A Type-2 Fuzzy Logic Based Goal-Driven Simulation for Optimising Field Service Delivery

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Abstract

This thesis develops an intelligent system capable of incorporating the conditions that drive operational activity while implementing the means to handle unexpected factors to protect business sustainability. This solution aims to optimise field service operations in the utility-based industry, especially within one of the world's leading communications services companies, namely BT (British Telecom), which operates in highly regulated and competitive markets.

Notably, the telecommunication sector is an essential driver of economic activity. Consequently, intelligent solutions must incorporate the ability to explain their underlying algorithms that power their final decisions to humans. In this regard, this thesis studies the following research gaps: the lack of integrated solutions that go beyond isolated monolithic architectures, the lack of agile end-to-end frameworks for handling uncertainty while business targets are defined, current solutions that address target-oriented problems do not incorporate explainable methodologies; as a result, limited explainability features result in inapplicability for highly regulated industries, and most tools do not support scalability for real-world scenarios. Hence, the need for an integrated, intelligent solution to address these target-oriented simulation problems.

This thesis aims to reduce the gaps mentioned above by exploiting fuzzy logic capabilities such as mimicking human thinking and handling uncertainty. Moreover, this thesis also finds support in the Explainable AI field, particularly

in the strategies and characteristics to deploy more transparent intelligent solutions that humans can understand. Hence, these foundations support the thesis to unlock explainability, transparency and interpretability.

This thesis develops a series of techniques with the following features: the formalisation of an end-to-end framework that dynamically learns form data, the implementation of a novel fuzzy membership correlation analysis approach to enhance performance, the development of a novel fuzzy logic-based method to evaluate the relevancy of inputs, the modelling of a robust optimisation method for operational sustainability in the telecommunications sector, the design of an agile modelling approach for scalability and consistency, the formalisation of a novel fuzzy-logic system for goal-driven simulation for achieving specific business targets before being implemented in real-life conditions, and a novel simulation environment that incorporates visual tools to enhance interpretability while moving from conventional simulation to a target-oriented model.

The proposed tool was developed based on data from BT, reflecting their real-world operational conditions. The data was protected and anonymised in compliance with BT's sharing of information regulations. The techniques presented in the development of this thesis yield significant improvements aligned to institutional targets. Precisely, as detailed in Section 9.5, the proposed system can model a reduction between 3.78% and 5.36% of footprint carbon emission due to travel times for jobs completion on customer premises for specific geographical areas. The proposed framework allows generating simulation scenarios 13 times faster than conventional approaches. As described in Section 9.6, these improvements contribute to increased productivity and customer satisfaction metrics regarding keeping appointment times, completing orders in the promised timeframe or fixing faults when agreed by an estimated 2.6%. The proposed tool allows to evaluate decisions before acting; as detailed in Section 9.7, this contributes to the 'promoters' minus 'detractors' across business units measure by an estimated 1%.

Scientific Dissemination

Publications

This work has resulted in the following publications:

- **E. Ferreyra**, H. Hagras, A. Mohamed, and G. Owusu, (2017) "A Type-2 Fuzzy Logic System for Engineers Estimation in the Workforce Allocation Domain", in *proceedings of the IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, Naples, Italy, July 2017.
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- Y. Zhou, A. Liret, J. Liu, **E. Ferreyra**, R. Rana and M. Kern, (2017) "Decision Support System for Green Real-Life Field Scheduling Problems", in: *Bramer M., Petridis M. (eds) Artificial Intelligence XXXIV. SGAI 2017*. Lecture Notes in Computer Science, Vol 10630. Springer, Cham.
  DOI: https://doi.org/10.1007/978-3-319-71078-5_30
- **E. Ferreyra**, H. Hagras, M. Kern, and G. Owusu, (2018) "Improving Goal-Driven Simulation Performance Using Fuzzy Membership Correlation Analysis", in *proceedings of the 10th Computer Science and Electronic engineering Conference (CEEC 2018)*, Colchester, UK, Sep. 2018.
  DOI: https://doi.org/10.1109/CEEC.2018.8674239

- **E. Ferreyra**, H. Hagras, M. Kern, and G. Owusu, (2018) "Enabling Field Force Operational Sustainability: A Big Bang-Big Crunch Type-2 Fuzzy Logic System for Goal-Driven Simulation", in *proceedings of the IEEE Symposium Series on Computational Intelligence (SSCI) (SSCI 2018)*, Bangalore, India, Nov. 2018.

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Award Contribution

My work contributed to the BT team winning the 2017 Outstanding Organisation Award given by the Institute of Electrical and Electronics Engineers (IEEE) Computational Intelligence Society (CIS). The award was given for the contributions and advances in intelligent systems for field force management.

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List of Acronyms

AI	Artificial Intelligence
AM	Agile Modelling
ANNs	Artificial Neural Networks
ASPs	Application Service Providers
BB-BC	Big Bang-Big Crunch
BB-BC T2FLS	Big Bang-Big Crunch Type-2 Fuzzy Logic System
BT	British Telecom
CAGR	Compound Annual Growth Rate
CI	Computational Intelligence
DARPA	The Defense Advanced Research Projects Agency
DNNs	Deep Learning Neural Networks
DSPs	Digital Service Providers
EC	Evolutionary Computation
EDA	Exploratory Data Analysis
FLSs	Fuzzy Logic System
FFC	Fuzzy Feature Contrast
FOS	Field Optimisation Suite
FOU	Footprint of Uncertainty
FS	Field Service
FSM	Field Service Management

FWSP	Field Workforce Scheduling Problem
GAs	Genetic Algorithms
GTI	Generalised Tversky Index
GDS	Goal-Driven Simulation
ISPs	Internet Service Providers
IT2FLS	Interval Type-2 Fuzzy Logic System
ITS	Intelligent Transportation Systems
LMF	Lower Membership Function
LSTM	Long Short-Term Memory
MC	Monte Carlo
ML	Machine Learning
OR	Operational Research
OSRM	Open Source Routing Machine
QoS	Quality Of Service
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SDP	Service Distribution Point
SLA	Service Level Agreement
SSPs	Storage Service Providers
sSWOT	The Sustainability Strengths, Weaknesses, Opportunities, Threats Analysis
T1MFs	Type-1 Membership Functions
TSPs	Telecommunication Service Providers
UMF	Upper Membership Function
VPN	Virtual Private Network Access

WA	Working Area
WAM	Workforce Asset Management
WSRP	The Workforce Scheduling and Routing Problem
XAI	Explainable Artificial Intelligence

List of Symbols

$\mathbf{R_i}$	Available resources
$\mathbf{J_i}$	Available tasks
$\mathbf{TRU_i}$	Actual travel utilisation
$\mathbf{TAU_i}$	Actual task utilisation
$\mathbf{CT_i}$	Closed tasks
$\mathbf{MHA_i}$	Man-hours allocated
$\mathbf{MH_i}$	Man-hours available
$\mathbf{MA_i}$	Missed appointments
$\mathbf{RJ_i}$	Number of resources with job
$\mathbf{ST}$	Number of scheduled tasks
$\mathbf{SSRA_i}$	Number of single skilled resources allocated
$\mathbf{MSRA_i}$	Number of multi skilled resources allocated
$\mathbf{SSRU_i}$	Number of single skilled resources unallocated
$\mathbf{MRU_i}$	Number of multi skilled resources unallocated
$\mathbf{PAS_i}$	Provision appointment scheduled
$\mathbf{PAU_i}$	Provision appointment unscheduled
$\mathbf{PNAS_i}$	Provision non-appointment scheduled
$\mathbf{PNAU_i}$	Provision non-appointment unscheduled
$\mathbf{PA_i}$	Provision appointment success
$\mathbf{PNA_i}$	Provision non-appointment success

$\mathbf{PAF_i}$	Provision appointment failure
$\mathbf{PNF_i}$	Provision non-appointment failure
$\mathbf{RAS_i}$	Repair appointment scheduled
$\mathbf{RAU_i}$	Repair appointment unscheduled
$\mathbf{RNAS_i}$	Repair non-appointment scheduled
$\mathbf{RNAU_i}$	Repair non-appointment unscheduled
$\mathbf{RA_i}$	Repair appointment success
$\mathbf{RNA_i}$	Repair non-appointment success

Chapter 1 - Introduction to Field Service Delivery

In supplier companies, field scheduling refers to allocating of a set of tasks to complete on a set of available workforces with different skills. The successful operation relies on efficient resource allocation. Therefore, the available workforce fulfils planned positions. This relation is commonly studied under the umbrella of operational workforce planning.

Field service delivery is the core in large firms that are capital-intensive with a strong focus on improving their competitiveness in volatile market environments. A non-exhaustive list of these firms includes telecommunication service providers, gas and water companies.

To remain competitive, organisations need to anticipate changes and act accordingly. Effective and efficient action is vital to protect enterprises' competitive advantage. Consequently, there is a need for tools that facilitate evaluating different alternatives. Commonly, these alternatives and their configurations are associated with scenarios [1]. These scenarios encapsulate the complex dynamics of the business operation. Scenario simulation and analysis enable decision-making before actually acting in the real-life operation [2]. Hence, the importance of robust, scalable and structured frameworks capable of handling target-oriented simulations.

One of the approaches that incorporates the simulation's benefits into solving optimisation problems is known as goal-driven simulation (GDS). Essentially, GDS attempts to find the value of a specific set of inputs to achieve the desired output by employing a simulation model. Traditional simulation allows us to create and evaluate "*what-if?*" scenarios. On the other hand, GDS allows performing "*how-to?*" scenarios. Consequently, GDS attempts to determine which inputs must be modified to accomplish the desired goal.

1.1 Objectives of the Thesis

This thesis investigates and develops an intelligent system capable of incorporating the conditions that drive operational activity while implementing the means to handle unexpected factors to protect business sustainability. The core aim is to develop a fuzzy logic system to enable GDS for optimising field service delivery operations while producing explainable models oriented to enable better human understanding. Hence, its relevance to the Explainable AI field. Fuzzy logic capabilities include mimicking human thinking and handling uncertainty; therefore, this thesis aims to develop an incremental explainable framework by exploiting these features and employing optimisation techniques are based on the big bang-big crunch algorithm. The objectives of the thesis are listed as follows:

- To explore the potential for innovative tools for the optimisation of field service delivery.
- To include risk-based simulation for sustainable field operations.
- To create a framework for modelling real-world uncertainties.

- To enable attainment of specific business targets within reasonable response times and accurate approximations.
- To disclose relevant accountability elements for the benefit of managers, planners and decision-makers.
- To predict service level performance metrics. In daily operations, service performance metrics such as appointment on arrival, appointed resources, completed on the first attempt, attrition rate, productivity, percentage of repair and completed on time are manually inputted by operational planners.
- To exploit machine learning algorithms to predict these measures and propose an optimised plan for operational use. Therefore, the development of novel computational intelligence techniques will support predicting and simulating the business's risk of resourcing decisions.
- To enable telecommunication service providers to de-risk investment decisions on the field force and improve operational performance.

This proposal focuses on bridging the following research gaps and inherent challenges in intelligent target-oriented simulation tools:

- Currently, there is a lack of integrated solutions that go beyond isolated monolithic approaches.
- There is a lack of end-to-end frameworks based on Agile Modelling where the principal aim is the model, along with its aims and capabilities.

- Current solutions that address target-oriented problems do not incorporate explainable methodologies, e.g., [2], [3] and [4]. As a result, their applicability is limited in highly regulated industries.

- Most tools do not provide a mechanism for scalability; therefore, analysis of complex models is limited.

- The lack of end-to-end structure from data generation, model applicability, uncertainty handling and business target definition.

Hence, the need for an integrated framework capable of generating "how-to?" scenario analysis that enables structured and explainable end-to-end target-oriented simulations.

1.2 Features of the proposed approach

The proposed approach spans a wide range of workforce allocation techniques to enable target-oriented simulations. Relevant features of this proposal are listed as follows:

- It is an end-to-end framework for dynamic data-driven membership function generation.
- It presents a novel fuzzy membership correlation analysis method to enhance performance for GDS models.
- It develops a novel fuzzy logic-based method to evaluate the relevant inputs and produce optimised rule-bases.

- It is a consistent optimisation method based on the big bang-big crunch algorithm to enable operational sustainability in the telecommunications sector.
- It employs a modelling technique that can scale real-life problems while obtaining consistent results.
- It implements a concise fuzzy logic-based model capable of keeping interpretability while uncertainty is gradually embedded into the model.
- It delivers a novel fuzzy-logic system to facilitate evaluating different scenarios for achieving specific business targets before being implemented in real-life conditions.
- It is a meticulous incremental framework for implementing "how-to?" scenarios, considering "what-if?" scenarios into the model loop.
- It is a novel and robust simulation environment that incorporates visual tools to enhance interpretability while moving from conventional simulation to a target-oriented model.

The improvements yield by the proposed techniques can be summarised as follows. The proposed system can model a reduction between 3.78% and 5.36% of footprint carbon emission due to travel times for jobs completion on customer premises for specific geographical areas. This translates to a reduction of 135 metric tonnes of carbon emissions for selected domains. Moreover, the proposed framework allows generating simulation scenarios 13 times faster than conventional approaches. These improvements contribute to increased productivity and customer satisfaction metrics regarding keeping appointment times, completing orders in the promised timeframe or fixing faults when agreed by an estimated 2.6%. Finally, the proposed tool allows to evaluate decisions before acting; this contributes to the ‘promoters’ minus ‘detractors’ across business units measure by an estimated 1%.

1.3 Thesis outline

This thesis consists of 10 chapters, as depicted in Figure 1.1. Each chapter is organised in subsections and conclusively discussed at the end of the corresponding chapter. The material of each chapter can be summarised as follows:

- Chapter 1 - introduced the field service delivery domain, which is the focus of this research. Successively, this chapter reported the research aims and objectives of this thesis. Subsequently, it outlined the research gaps that this research aims to bridge. Next, this chapter reported the features of this research regarding the novelty and the contributions. Finally, this chapter presented the structure of the thesis.
- Chapter 2 - introduces sustainable field service operations and risk management by analysing field service operations and their main components. Successively, this chapter provides an overview of the elements for sustainable service operations and reviews risk management elements.
- Chapter 3 - provides an overview of fuzzy logic, which is the foundation of this thesis. Then this chapter introduces the concept of a fuzzy set and its derivate types. Successively, this section provides an overview of the types of fuzzy logic systems and the main operation from their

architectural angles. Subsequently, this chapter introduces an alternative classification of fuzzy logic systems. Finally, this chapter outlines relevant real-world applications of fuzzy logic systems.

- Chapter 4 - provides a review of explainable AI (XAI) by outlining the main XAI strategies available in the literature. Successively, this chapter discusses the role of AI-based decision support systems in the industry. Finally, this chapter showcases the role of fuzzy logic for human understanding of problem-solving.
- Chapter 5 - introduces to GDS approach and its role in field service operations. Then, this chapter reviews “what-if?” and “how-to?” scenario analysis. Subsequently, this chapter explains the need for GDS in BT. Finally, this chapter defines simulation scalability.
- Chapter 6 - creates a concise approach to create a data-driven model for decision-making by introducing the different categories available in the literature. Successively, this chapter outlines a data-driven model by covering the topics of data acquisition, data exploration and pattern discovery. Subsequently, this chapter defines a strategy to leverage conventional simulation to support GDSs.
- Chapter 7 - introduces the first phase in constructing the proposed GDS model by outlining an agile modelling approach for fuzzy logic systems (FLSs). Next, this chapter constructs an initial type-1 FLS. Then, this chapter extends the achieved type-1 to type-2 FLS. Finally, this chapter presents the experiments, analyses the results, discusses the achievements, and points out the shortcomings.

- Chapter 8 - enhances the initial fuzzy logic systems by incorporating a clustering method to construct the membership functions efficiently. Successively, this chapter implements Gaussian membership functions for leveraging data attributes for better results. Successively, this chapter develops a strategy for inputs and outputs selection based on fuzzy correlations. Subsequently, this chapter introduces a similarity approach. Finally, this section develops the experiments, analyses the results, and presents the enhanced type-2 fuzzy logic system's benefits for GDS.
- Chapter 9 - focuses on optimising the proposed GDS model by introducing the big bang-big crunch algorithm and defining a methodology based on this optimisation procedure. Successively, this chapter introduces an interactive visualisation tool to depict decision-making. Then, this chapter formalises the main elements of the framework for GDS. Finally, this chapter develops extensive scale experiments by defining the benchmark criteria, analysing the results, and discussing the final version of this proposal's benefits.
- Chapter 10 - presents the summary of achievements, outlines the contributions of this thesis and visions future course of action.

Figure 1.1 provides the thesis structure by detailing direct links between chapters (see solid lines) and chapter dependencies (see dotted lines). It is noteworthy that the agile modelling implemented in this thesis allows achieving a clear layout where direct links show incremental knowledge building. Similarly, chapter dependencies illustrate the support in the development of further chapters.

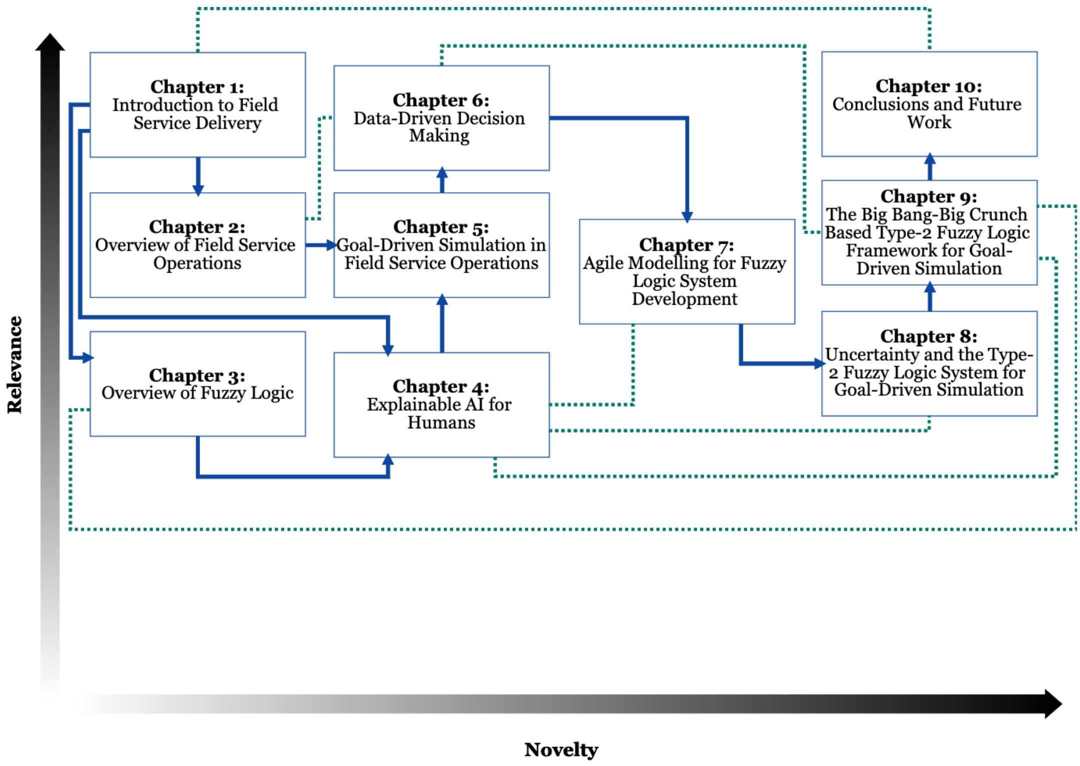

Figure 1.1. Thesis structure showing direct links between chapters (solid lines) and chapter dependencies (dotted lines).

Correspondingly, in the reported diagram, each chapter is organised according to its relevance and novelty. Finally, supporting material is reported in the following appendixes:

- Appendix A provides an overview of information sharing rules in the telecommunications sector by providing a sense of the regulation of data protection, data access and data sharing.

- Appendix B provides a detailed step by step generation of the type-1 membership for the number of available tasks by showcasing an example for equally spaced triangular fuzzy sets.
- Appendix C provides detailed results comparing different systems trained and tested in the final iteration of the proposed framework by each geographic area involved in the large-scale experiments.

Chapter 2 - Overview of Field Service Operations

Field service (FS) encompasses a set of activities to complete work tasks on any location [5]. The operations deployed to carry out those tasks depend on the nature of the businesses and organisations. Commonly, the staff that carries out the required work is integrated by a skilled workforce. *Field service operations* align the work to do with skilled staff. A successful alignment between these two elements directly impacts productivity levels, hence companies' competitive advantage. The effectiveness of field service operations affects customer satisfaction and profitability of organisations [6].

Successful field operations require considering the uncertainty factors that will adversely impact corporations and their business objectives. For most real-world scenarios, this is not trivial. Mainly due to the impreciseness native in future risk evaluations [7]. In the scope of this thesis, the risk management strategy encompasses the following elements: (1) model uncertainty into the architectural framework, (2) provide a mechanism for accountability and (3) to monitor and safeguard companies' business sustainability.

This chapter provides a field service operations overview by outlining relevant elements in supplier companies, particularly in Telecommunication Service Providers (TSPs). Next, this section provides an overview of sustainable service operations by focusing on relevant research trends in the sustainable operations domain. Finally, this chapter reviews the elements conforming to the strategy for risk management for sustainable service operations.

2.1 Field service operations ecosystem

Field service operations allow organising jobs to be completed and the available resources. Field service operations are particularly relevant to utility companies with core business activities related to new installations, on-site maintenance works and repairs at customer premises. For these companies, resources include staff with different skill levels. This skill categorisation plays an essential role in deciding the staff suitability for a specific job. As a result, field service operations ensure that the available workforce fulfils planned positions.

However, these principles are not exclusive to utility companies where human resources are essential. These also apply to software and hardware-based services such as cloud computing. *Cloud computing* implements mechanisms to access computer capabilities via the Internet [8]. In cloud computing, the jobs can be represented by the requested on-demand network access. Similarly, the available resources are organised in application architectures based on networks servers, storage, applications, and services. Besides, resources in manufacturing industries encompass machinery and specific technology for large scale production of goods.

Moreover, new hybrid manufacturing models are emerging, such as cloud manufacturing [9]. *Cloud manufacturing* combines cloud computing, artificial intelligence, big data, and the Internet of things to facilitate manufacturing resources globally. This paradigm is employed for products with complex processes, particularly in the aviation and aerospace industries [10].

Field service operations can vary widely accordingly to the industry, the frequency of the requests, and the resource type (e.g. multi-skilled staff, hardware-based or software-based). Each scenario handles its inherent complexity; consequently, as the organisation size increases, the field service operation's effective management increases. As a result, various technology-driven methodologies have been developed to transform the field service and operations landscape [11]. Consequently, various automation levels have reached a certain level of maturity; this enables efficient schedules for the completion of jobs among different geographic locations.

Relevant automation features in the field service operations ecosystem include workforce asset management, service level agreements, field service geo-location, workforce scheduling and field service management platforms. Each feature solves an increasing business need for integrated management tools. As a result, each element feeds the scheduling capability, which has become a core element for large scale workforce management solutions across various industries. The following subsections provide an overview of these features.

2.1.1 Workforce asset management

To accomplish the organisations' business goals, companies must effectively manage four main aspects. First, the acknowledgement that every employee can contribute to the achievement of the institutional targets. Second, the staff is more than a human resource; therefore, the staff is a vital differentiator of an organisation. Third, companies must provide conditions for improving staff performance. Fourth, operational risk must be minimised.

From a strategic action plan, workforce asset management enables organisations to handle effectively and efficiently the four mentioned aspects. Therefore, workforce asset management (WAM) is defined as a cross-disciplinary speciality focused on the alignment of the staff with the company's strategic vision. This approach aims to maximise productivity while enforcing compliance across the organisation. In parallel, WAM controls the cost of labour while maintaining the workforce engaged [12].

2.1.2 Service level agreement

Service level agreements (SLAs) are written contracts that state the service level to be expected by customers from a supplier. Generally, SLAs outline the corresponding metrics to assess the service. SLAs are a common practise in the service provider operation [13].

A *service provider* is broadly defined as an organisation that delivers solutions and services to the mass-market and other organisations [14]. Examples are the application service providers (ASPs) such as cloud computing and software as a service, storage service providers (SSPs), internet service providers (ISPs) including local, regional and national levels, digital service providers (DSPs), including streaming video and online music and telecommunications service providers (TSPs) which traditionally deliver telephone and mobile wireless communication services.

Notably, in the TSPs domain, SLAs facilitate achieving Quality of Service (QoS) by defining what is offered and how it is evaluated. *QoS* encompasses a set of specific user requirements. Generally, the most considered QoS parameters in the TSPs are delay, jitter, packet loss and throughput. Delay refers to the latency of which an information package will reach its destination. Jitter indicates the variation in the delay. Packet loss occurs when data packages fail to reach their destination. Furthermore, throughput refers to the rate at which a data package is sent, received or processed in a determined time-lapse [15].

When SLAs are met successfully, they are a vehicle for customer acquisition and customer retention. Otherwise, SLAs could affect companies' competitive advantage [16]. Therefore, the design of SLAs must be carefully aligned to the business goals and the companies' capabilities [17]. In the business operation, SLAs impact service delivery and operational cost [18]. Hence, the importance of monitoring SLAs in the service fulfilment.

2.1.3 Field service geo-location

A key element for effective and efficient field service operations is to divide the territory where the organisation operates. This approach is relevant when the workforce completes work tasks at the customer premises. This situation can be observed in the utility sector such as water, electricity and gas firms, mobile healthcare workers or courier personnel.

Large firms must carefully align their field workforce with their geographical operation. Commonly, global firms structure their operation by countries. Then, a micro design approach is recommended to drive the field service geo-location strategy [19]. A micro design approach consists of building geographical hierarchies, where the bottom of the structure is the smallest possible unit for work allocation. Large organisations could result in structures with a high degree of branching. In practice, this enables maintenance and redesign on demand. Figure 2.1 depicts a resulting hierarchy for a large TSP that operates in the UK.

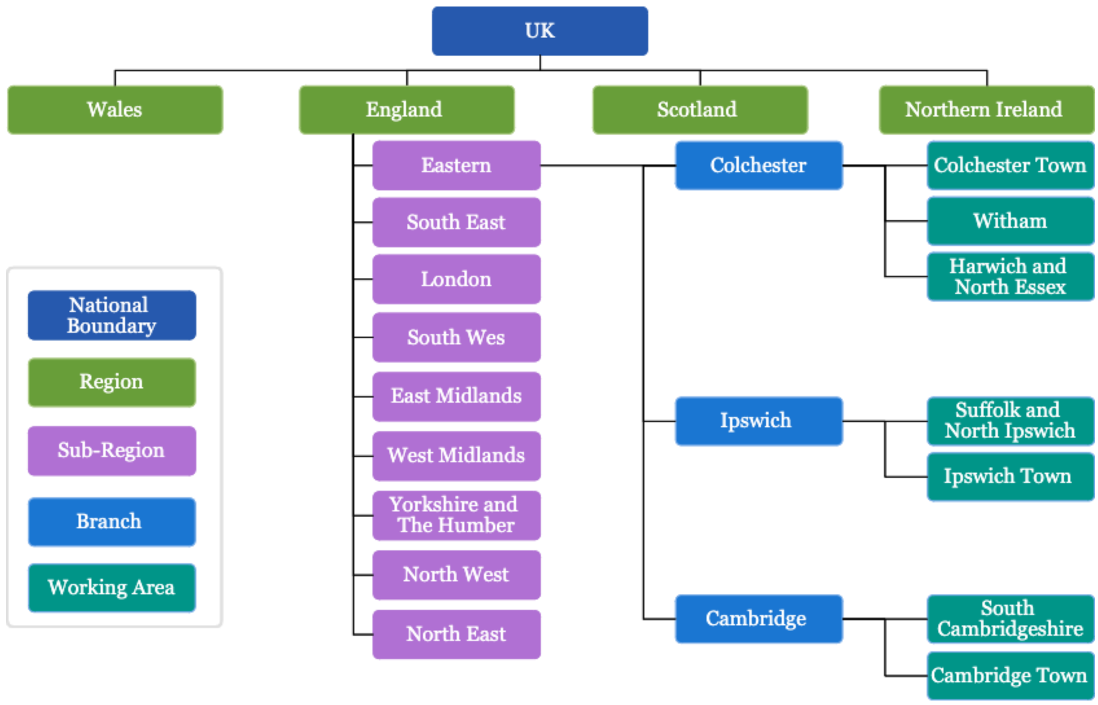

Figure 2.1. A simplified example of a geographical hierarchy (Source: [20])

As can be observed, working areas are the smallest unit for work allocation. Branches are the result of grouped working areas. Similarly, sub-regions encompass grouped branches. Correspondingly, regions group sub-regions. Finally, a national boundary is integrated by the mentioned subordinates.

2.1.4 Field workforce scheduling

Field workforce scheduling consists of conforming teams of staff and assigning tasks to each team. The complexities derived from this aim are studied under the *field workforce scheduling problem* (FWSP).

FWSP has three key elements [21]. First, *multi-skill categorisation*, which aligns the different skill requirements for completing a task with the workforce skills set. Second, *geographical dispersion* refers to the need to complete the work tasks at the customer premises. Therefore, the skilled workforce must be provided with a list of locations to visit. These lists of locations are known as routes. The efficiency of these routing solutions is studied under the *workforce scheduling and routing problem* (WSRP). Third, *multi-objective functions*, which address the simultaneous optimisation of different objective functions. In real-world business operations, these are mostly conflicting objectives functions resulting in complex optimisation problems. Example of conventional objective functions are maximising product reliability [22], minimisation staff size [23], minimising operational travel [24], minimising over time [25], minimising total completion time [26], and maximising staff utilization [27] among others.

The formalisation of FWSPs encompasses the number of objective functions and the different approaches employed for their solutions. For instance, Alsheddy and Tsang [28] first articulated a bi/multi-objective problem that involved scheduling a multi-skilled workforce to geographically dispersed tasks. This research modelled a management concept (i.e. employee empowerment) in the form of an optimisation problem (i.e. workforce scheduling). The model consisted of four characteristics, namely simplicity, flexibility, fairness and applying a win-win approach. As a result, the multi-objective problem consisted in finding a balance between employees' satisfaction and companies' interests and solved it by a local guided search approach by satisfying about 58% of plans instantiated by all employees, with a trade-off of 7% of the main objective.

Braekers et al. [29] analysed the trade-off between operating cost and service level. This research modelled factors such as qualifications, working regulations, overtime costs, travel costs, time windows, and client preferences. A distinctive characteristic of this approach is that the scheduling problem is approached as a bi-objective problem in itself. The problem was solved by a metaheuristic algorithm, embedding a large neighbourhood search heuristic in a multi-directional local search framework. The results showed that service providers face a considerable trade-off between costs and client convenience. However, cost variation between 5 and 10 per cent already reduced the inconvenience in the range between 27 and 39 per cent.

Urquhart and Fonzone [30] studied solutions for the WSRP by modelling a three-objective optimisation problem focused on minimising financial cost, CO_2 emissions and car use. This work built a Pareto front of non-dominated solutions, which represented solutions with a particular trade-off between objectives. A shortcoming found was a large number of solutions; the authors addressed this drawback by an evolutionary algorithm-based approach. This technique enabled the ability to apply custom filter criteria. As a result, the solution facilitated producing a small subset of solutions quicker and tailored as the end-user fits.

Farina and Amato [31] studied multi-criteria search problems with more than three objectives and found that the Pareto optimality definition is unsatisfactory for these cases. Moreover, Pareto optimality does not numerically express the common knowledge that a decision-maker would consider when deciding on such problems. This research offered fuzzy-based definitions of optimality for modelling concepts such as equal, smaller, higher, and numerically to emulate decision maker thinking. As a result, this fuzzy reasoning illustrates that optimality definition can be applied to both continuous optimisation and discrete decision making.

Recently, Starkey et al. [32] deployed a type-2 fuzzy logic solution for many-objective problems for optimising a mobile workforce. The aim of the optimisation focused on skills suitability, location and time while modelling the uncertainty in the environment. The application implemented a genetically optimised type-2 fuzzy system to improve the results, which were initially generated by a multi-objective optimisation algorithm. As a result, the objective improvement was approximately 30% regardless of the number of objectives, on average.

A survey conducted recently on the wide variety of field workforce scheduling applications identified the following real-world problem domains: health care, home care, scheduling technicians, security personnel routing and rostering and workforce allocation [33]. Although these examples do not represent all possible domains, they illustrate the relevance of field workforce scheduling cross-industries. Moreover, Gartner forecasted that in 2022, over 50% of field service providers would need to enable additional communication channels because of offering new specialised customer experiences and services. Furthermore, only 30% of field service providers will be ready to deploy intelligent support capabilities to their field service management platforms by 2022 [34]. Hence, the importance of studying and disrupting the field service operations ecosystem.

2.1.5 Field service management platforms

Field service operations aim to dispatch skilled staff to customer premises to carry out specialised services. Non-exhaustive examples of such services include providing installation, repairing or maintenance for equipment or systems and providing health or home care. Typically, these services are assessed and monitored by predefined contracts known as service level agreements (SLAs). *Field service management* (FSM) encompasses the activities required for their effective execution and control. Commonly, these are automated and supported by FSM platforms. FSM platforms refer to automated software-based solutions that hasten collaboration between all the field operations processes, aiming to increase productivity.

FSM platforms are particularly relevant to capital-intensive companies with a strong focus on improving their service delivery. FSM requirements can vary widely depending on factors such as company size (e.g. small, medium, and large-sized enterprises), deployment type (e.g. on-premise and cloud) and industry vertical (e.g. telecom, healthcare, transportation and logistics, energy, and utilities). Consequently, a large variety of solutions have been tailored to target these different use cases. As a result, these drive a growing global FSM market, which is expected to reach a compound annual growth rate (CAGR) of 16.9% from 2019 to 2026 [35].

Commonly, FSM platforms support six essential functionalities of the field services operations processes. These are work order debrief, staff entitlement, demand management, work planning, operations, and analytics/integration. Each functionality is implemented in different depth across three main categories. These are field delivery, back-office operations and triage and dispatch centre.

Recognised third-party vendors are active players in this market, including Oracle Corporation, Microsoft Corporation, Salesforce, and SAP, among others. However, various research groups and different companies have been developing their in-house FSM solutions. Undoubtedly, a convergence of technologies has facilitated advances in the field service operations landscape. Examples of these technologies include mobile devices ubiquity, connected field service via the Internet of Things (IoT), Machine Learning (ML), and increased computer processing. As a result, real-life field service operations problems have been successfully solved by cohesive approaches. For example, recently, a mixed-integer programming model was proposed to solve a multi-skill workforce and routing problem faced by an energy distribution company in Turkey [36].

Another example of an in-house FSM solution is the one developed by British Telecom (BT) in 1996. Initially, BT's FSM platform implemented a combination of heuristics search and constraint-based reasoning. This solution was rolled out nationally in 1997 [37]. Later, in 2005, BT launched the Field Optimisation Suite (FOS) containing five modules. These modules can be described as follows: field forecast, which focuses on demand forecasting; field plan, which provides medium to long-term resource plans; field schedule, which focuses on work allocation; field reserve, which provides reservation capabilities for future demand and field people, which handles the staff attendance and skills [5]. FOS was initially supported by techniques such as constraint satisfaction for problem modelling and heuristic searches for problem-solving [38]. Later, in 2008, diverse resource planning strategies, forecasting and tactical resource allocation were incorporated [21]. However, these techniques presented certain limitations related to the efficient management of unprecise data.

Recently, solutions based on fuzzy-genetic and type-2 fuzzy logic to mitigate uncertainty were incorporated. For instance, a fuzzy-genetic based system to establish coarse-grained resource deployment for medium-term planning periods was produced [39]. This work employed compatibility measures between resources and the allocated tasks. The experimental results outperformed a baseline hierarchical fuzzy logic-based planner in metrics including resources deployment, covered tasks, tasks per resource and resource travel time by 71.43%, 3.49%, 3.78% and 37.37%, respectively.

Subsequently, a hierarchical genetic interval type-2 fuzzy logic-based planner to generate daily schedules was introduced [40]. This work focused on improving efficiency related to tasks allocation based on one UK geographical area over seven days. The results outperformed its counterpart hill-climbing heuristic-based search techniques in measures including utilised resources and covered tasks by 13.71% and 15.93%, respectively.

Moreover, the optimal allocation of field service engineers to their working areas was studied by applying a genetic type-2 fuzzy logic-based approach [20]. This work improved the original working areas in reducing travel by 60% and reducing un-balanced patches by 70% for the same coverage and utilisation references.

2.2 An overview of sustainable service operations

Sustainability has been defined based on different conceptual nuances of sustainable terminology. Principally, these slight differences are threefold. First, at the societal level, the term *sustainable development* refers to the ability to satisfy current needs without compromising their future fulfilment [41]. Second, at the corporate level, the term *corporate sustainability* refers to the adoption of business strategies to meet current needs while protecting and sustaining natural and human resources that will be required in the future [42]. Third, at the management level, the term *corporate social responsibility* refers to the benefit from synergies among economic, environmental and social aspects while satisfying current needs [43].

Global concerns on sustainability have resulted in a call for action to the international community. Broadly, these concerns include human-induced climate change and economic growth while protecting the environment, among others. As a result, since 1972, the United Nations has facilitated a series of meetings to address these concerns. These meetings are known as Earth Summits [44]. From 2015, the outcomes of these meetings work towards plans of actions aligned to 17 sustainable development goals with 169 associated targets as described in the Agenda 2030 [45].

In the field services operation context and for this thesis, *sustainability* is defined as the effective allocation of resources while considering companies' financial situation, social and environmental risk and regulatory compliance.

2.2.1 An overview of sustainable operations research trends

This section aims to provide a big picture of the research interests related to sustainable field operations. In this context, a survey performed a citation analysis to determinate the research interest in publications on this domain. In this study [46], the authors identified 52 relevant articles within the scope of sustainable field operations. These articles were disseminated between 2003 and 2018 in an academic journal published by the Institute for Operations Research and Management Sciences.

Subsequently, data collected in January 2019 showed that these 52 papers were cited 2,789 times across different academic journals. Subsequently, the citation profile was created as follows. First, the authors created five streams for paper classification. These are Closed-Loop Supply Chain, Low-Carbon Economy, Environmental Management and Performance, Innovation, and Social Responsibility. Therefore, each of the 52 papers was classified accordingly. Next, the authors aggregated various fields of knowledge into five areas of study. These five areas of study include Operational Research (OR), Business-non-OR, Science and Engineering, Environmental Research, and Economics. Figure 2.2 reports the citation profiles for each of the five research streams by area of study. As can be observed, each stream is broken down into the percentage of citations obtained in each area of study.

Besides any potential bias inherent in this work, relevant insights for this section can be drawn as follows. The sustainable operations research theme has noticeable interest from other areas of study beyond operational research itself, specifically in Environmental Research and Science and Engineering. Closed-Loop Supply Chain and Social Responsibility streams are particularly relevant for the Operational Research area of study. Research in sustainable operations is also of interest to the business non-related to operational research, labelled as Business-non-OR.

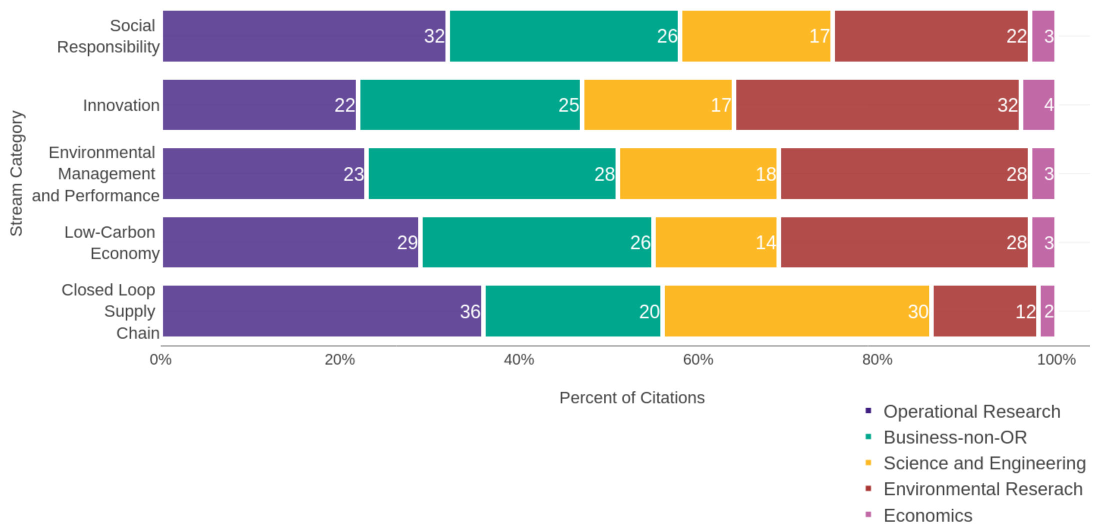

Figure 2.2. Citation profile by area of study and stream category (Source: [46])

2.2.2 Sustainability-related legislation

Sustainability concerns have enacted various legal aspects around the world. As a result, some governments have committed those proposals to various pieces of sustainability-related legislation. These regulations cover a wide range of facets. However, the following examples highlight only the relevant aspects of the sustainable field operations context:

- The Environmental Protection Act 1990[1], which contains provisions for ***air pollution***, among other matters.
- The Environment Act 1995[2], which makes provisions concerning ***air quality***, among other issues.
- The Climate Change Act 2008[3], which aims the reduction of targeted ***greenhouse gas emissions*** by the year 2050.

[1] http://www.legislation.gov.uk/ukpga/1990/43/contents
[2] http://www.legislation.gov.uk/ukpga/1995/25/contents
[3] http://www.legislation.gov.uk/ukpga/2008/27/contents

- The Energy Savings Opportunity Scheme[4], which is a mandatory energy assessment scheme for organisations in the UK that meet specific qualification criteria. It focuses on how ***energy*** is used in buildings, ***transport,*** and industrial operations.

As highlighted, the listed regulations cover air pollution, air quality, greenhouse gas emissions and energy used in transport. These policies are particularly relevant for field service operations. Specifically, because travelling to customer premises implies carbon emissions. Similarly, field service operations demand the use of transportation units. Consequently, medium and large-sized enterprises have incorporated these sustainability aspects into their strategic priorities [47]. In this regard, BT developed recently an intelligent solution for real-life field service operations that focuses on carbon dioxide (CO_2) emissions minimisation, heterogeneous vehicle fleet, time window constraints, and skill matching constraints. Part of the work presented in this thesis contributed to this intelligent tool for enabling sustainable operational actions, such as the adaptation of greenfield-service decision support models while monitoring the footprint levels of scheduling and routing plans.

2.3 Risk management for sustainable service operations

Organisations that pursue integrating sustainability into their core business objectives need to identify risks, understand and evaluate their impact, and

[4] https://www.gov.uk/guidance/energy-savings-opportunity-scheme-esos

integrate them into strategic decision making. However, global markets are moving into a new era in which companies are shifting towards sustainable operations while fulfilling human needs [48]. Consequently, traditional risk management approaches may no longer hold. In this context, recently, a strategic set of guidelines on managing risk was arranged by the International Organization for Standardization; these are known as the ISO 31000:2018 standard [49].

In the ISO 31000:2018 standard, the variation between the expected and the actual outcome due to uncertainty is defined as *risk*. When the variation is positive, it can result in opportunities. Otherwise, it can result in threats. The coordination of activities to effectively handling risk is described as *risk management*.

2.3.1 Identifying risks

A crucial factor in delivering sustainable service operations is the ability to spot the degree of future uncertainty scenarios. Uncertainties can come from different sources; therefore, capturing all types in advance is practically impossible. However, undertaking risk identification can mitigate this problem. In this context, analysis tools can support identifying risks.

In practice, sustainable service operations are much broader than environmental issues. In this regard, this thesis implements an approach based on the sustainability Strengths, Weaknesses, Opportunities, Threats analysis (sSWOT) framework [50].

The sSWOT framework can help to drive action and collaboration on environmental challenges by identifying business risks and opportunities. The adaptations of this work are twofold. First, the inclusion of operational uncertainty. This related to productivity on long term time horizons, unknown demand, and the alignment with global sustainability trends. Current global sustainability trends involve halving emissions, sustainable consumption, supply chain transformation, protecting biodiversity, investing in employee wellbeing, among others. Second, scenario simulation modelling as a decision-making support tool, which, enables evaluation capabilities before implementing actions.

2.3.2 Understanding and assessing the impact

Once organisational risks are identified, a better understanding of the implications is essential. In practice, there are some differences between assessing the impact of traditional risks compared to those arising from sustainable service operations. Table 2.1 broadly summarises the differences for each element involved in their assessment.

Various approaches are suitable to assess the impact of risks. These include qualitative risk assessment, quantitative risk assessment, trend impact analysis, Monte Carlo simulation, spatial analysis, and scenario modelling, among others. Each approach has its applicability depending on each situation. Technical differences between these approaches consist of the grade of complexity and the level of innovation.

Table 2.1– Some differences between assessing the impact of traditional risks compared to those arising from sustainable service operations.

Element	Traditional risks	The risk from sustainability-based approaches
Business impact	Impact in certain areas inside the organisation.	Impact affecting various organisation levels.
	Impact on a limited number of stakeholders outside the organisation.	Impact cascading to many levels outside the organisation.
Measurement	Predominantly financial.	Qualitative and quantitative.
Impact and likelihood	It can be modelled base on historical data.	Complex to assess and model, commonly, requires scientifically based approaches.
Factors considered	Limited to manage uncertainty.	Requires broader interdependencies such as operational conditions, customer requirements, and staff skills set, among others.
Cost	Sensible estimation.	Complex to forecast due to uncertainties, including how the threat or opportunity will manifest.

As depicted in Figure 2.3, scenario modelling presents a reasonable balance between innovation and complexity. Thus, the approach presented in this thesis lies in the scenario modelling approach.

Scenario modelling consists of the generation of future scenarios that facilitate the testing of different conditions and their potential solutions [51]. This approach can be used to determine how the business need to evolve to meet future operational conditions, to evaluate appraisals of the cost-benefit of different possible actions, to ascertain the positive or negative effect of future outcomes, and to prioritise further actions.

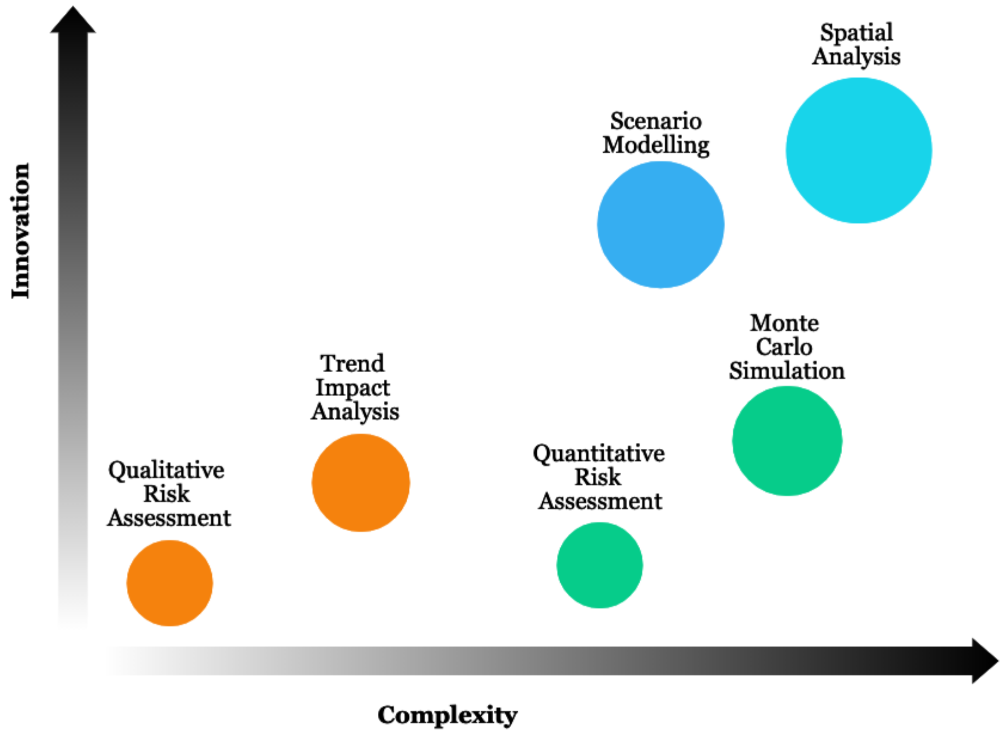

Figure 2.3. Degree of complexity innovation by assessment methods (Source: [51])

Benefits of the scenario modelling approach include taking advantages of external data sources by embedding them into various configurations, facilitating collaboration due to relative complexity, enhancing communication and understanding due to innovative implementations, and flexibility to feed other assessment approaches.

Challenges in scenario modelling include consistency in data collection phases, systematic minimisation of assumptions, onboarding enough points of view to produce balanced overviews, generating realistic scenarios requires a deep understanding of the underlying operational process and the alignment with the intrinsic risks.

2.3.3 Integrating risk into decision making

To integrate risks into decision making, organisations must have already identified the potential risks, understood, and assessed their impact. In the context of the work presented in this thesis, the following aspects should be considered. First, the uncertainty embedded in the model is derived from the available data. Second, the quality of the data fed into the model drives the generation of realistic scenarios. Third, any action that modifies the business operation should benefit from multiple scenario generation. As a result, if the data satisfy the requirements for realistic scenario generation, then increasing its availability will enhance the model.

Available data and risk understanding have a direct association; for example, higher data with increased understanding can reflect risks systematically into the model. Similarly, lower data with increased understanding can result in the identification of the risk. However, it is not possible to reduce the uncertainty factors before they influence the model [52].

2.4 Discussion

This chapter has provided an overview of the role of field service operations within the utility sector, extended the fundamental field service principles to software and hardware-based services, and listed the elements that conform the field service operations ecosystem. Subsequently, it introduced the definition of sustainability, reviewed the sustainable operations research trends, and outlined relevant sustainability-related legislation. Finally, this chapter provided the definition of risk, reviewed the role of risk management for sustainable service operations, outlined a risk classification, provided a method to identify risks, reviewed the importance of understanding and assessing the impact of risk arising from sustainable service operations, and explained the association between available data and risk understanding as a mechanism to integrate risk into decision making.

Each section of this chapter has devoted to providing the core elements from the business point of view that encompass the applied research scope of this thesis. To recapitulate, the focus of this thesis is the field service in the telecommunications industry, notably within BT as a critical TSP in the UK territory. Overall, the core business activities related to new installations, on-site maintenance works and repairs at customer premises. These activities are carried out by multi-skilled engineers. The service delivery is expected to meet certain expectations, such as QoS, among others. These levels of service to be expected by customers from BT are defined in contracts known as SLAs. To provide an effective and efficient field service operation, BT employs a micro design geo-location strategy to divide the territory into small units for work allocation. This work allocation encompasses a multi-skill categorisation, particular geographical dispersion, and multi-objective functions. BT developed an in-house FSM solution, which has been in constant development and evolution for almost 25 years. Hence, the work developed in this thesis will act as satellite support of this in-house FSM solution while approaching it as an opaque-box.

Additionally, elements of sustainable field services operations being tackled in this thesis include CO_2 emissions minimisation, heterogeneous vehicle fleet, time window constraints, and skill matching constraints. These elements are relevant, because as reviewed in Section 2.3, environmental risks represent the highest likelihood for 2020. Moreover, to understand and estimate the risk impact, this thesis employs a scenario modelling approach. Scenario modelling facilitates determining how the business need to act to meet future operational conditions. Lastly, this thesis presents a data-driven intelligent solution; therefore, as depicted in Section 2.3.3, data play a fundamental role in satisfying the requirements for realistic scenario generation.

Finally, a noteworthy expectation outlined in Section 2.1.4 indicates that only 30% of field service providers will be ready to deploy intelligent support capabilities to their field service management platforms by 2022. Hence, the relevance of studying and disrupting the field service delivery through the work presented in this thesis.

The following chapter will introduce the literature on fuzzy logic, including a brief overview of the history that provided the foundations of fuzzy set theory, the types of fuzzy sets, some typical applications of fuzzy systems, and recent advances in intelligent solutions based on fuzzy logic applied to the field service delivery domain.

Chapter 3 - Overview of Fuzzy Logic

Fuzzy Logic (FL) is one of the pillars of soft computing methods. FL can deal with the imprecise nature of human cognition by quantitatively representing vague terms [53]. FL reveals its underlaying elements for knowledge representation. In the broadest sense, knowledge in FL is represented between rules and membership functions. This approach naturally aligns with the purpose of XAI. FL gives insight into the relationships between inputs and outputs.

This chapter provides an overview of fuzzy logic, starting with a brief review of the core terminology followed by the type of fuzzy logic systems. Subsequently, this chapter outlines some typical applications of fuzzy systems. Finally, it lists relevant advances in intelligent solutions based on fuzzy logic applied to the field service delivery domain.

3.1 Fuzzy sets

Fuzzy sets are the foundation for understanding fuzzy logic. Fuzzy sets facilitate translating a precise measurement into a degree of belonging in a linguistic label [54]. When Professor Zadeh introduced the concept of fuzzy set [55], there was no distinction between any fuzzy set type. However, the scientific community referred to these concepts as type-1 fuzzy sets. Later, in 1975

Professor Zadeh introduced type-2 fuzzy sets. Type-2 fuzzy sets are a formal extension of their type-1 counterpart [54]. The following subsections will review the main characteristics of these fuzzy sets.

3.1.1 Type-1 fuzzy logic sets

Type-1 fuzzy logic sets imitate the human inclination to group numeric scales by using linguistic terms. Commonly, these terms provide an adequate understanding when a specific distinction is not required [54]. Linguistic terms describe measurements in a human rationale, for example, to describe speed, we can use terms ranging from "slow" to "fast". Similarly, to describe altitude, we can use words such as "low" or "high". Each type-1 fuzzy set is valid in a subset of the universe of discourse X, and it is represented by a label A_i characterised by a *membership function* (MF). The MF correlates a two-dimensional function that defines the degree of association of a numeric value x under the corresponding linguistic label using a precise number in the range $[0-1]$. The degree of association of x in A is denoted as $\mu_A(x)$. Formally, A is entirely characterised by [56]:

$$A = \{(x, \mu_A(x)), \forall x \in X\} \tag{3.1}$$

The universe of discourse X can either be continuous or discrete. When it is continuous, A is entirely characterised by [57]:

$$A = \int \mu_A(x)/x \tag{3.2}$$

Correspondingly, when the universe of discourse X is discrete, A is entirely characterised by [57]:

$$A = \sum \mu_A(x)/x \tag{3.3}$$

Geometrical structures represent MFs. Figure 3.1 depicts some shapes regularly employed by type-1 fuzzy sets. These geometrical shapes include triangular (see A), trapezoidal left shoulder (see B), and trapezoidal right shoulder (see C) among others. As can be observed, MFs explicitly define the corresponding type-1 fuzzy sets. Therefore, in the design of type-1 fuzzy sets, it is frequently accepted the absence of any ambiguity [58].

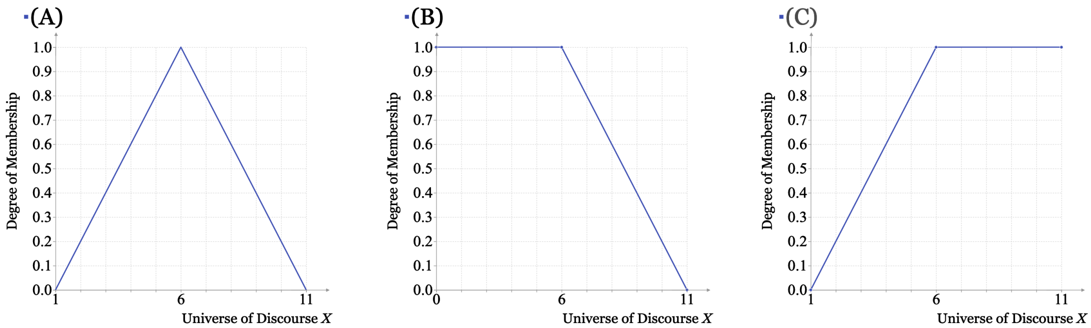

Figure 3.1. Examples of type-1 MFs: (A) triangular, (B) trapezoidal left shoulder and (C) trapezoidal right shoulder (Source: [58]).

3.1.2 Type-2 fuzzy logic sets

The need for type-2 fuzzy sets was driven by the limitation observed in type-1 fuzzy sets, where the MFs are defined without incorporating any uncertainty on their parameters [54]. Consequently, type-2 fuzzy logic sets include uncertainty by incorporating an additional degree of fuzziness. This degree of fuzziness is also known as a degree of freedom.

Figure 3.2 offers an overview of type-2 fuzzy sets and these new concepts. Where, trapezoidal membership functions are present with their corresponding linguistic labels, i.e. low, medium and high. The highlighted fuzzy set illustrates that the blurred region annotated as Footprint of Uncertainty (FOU) is bordered by two MFs. These are the upper and the lower membership functions, also known as secondary memberships. It is noteworthy to observe that the dotted lines represent the membership functions concerning the type-1 fuzzy sets. These are commonly known as primary memberships. The blurred area in the depicted type-2 fuzzy set expresses the additional degrees of freedom. In practice, these degrees of freedom can handle uncertainties induced by noisy data and fluctuating conditions frequently found in practical and real-world applications [54].

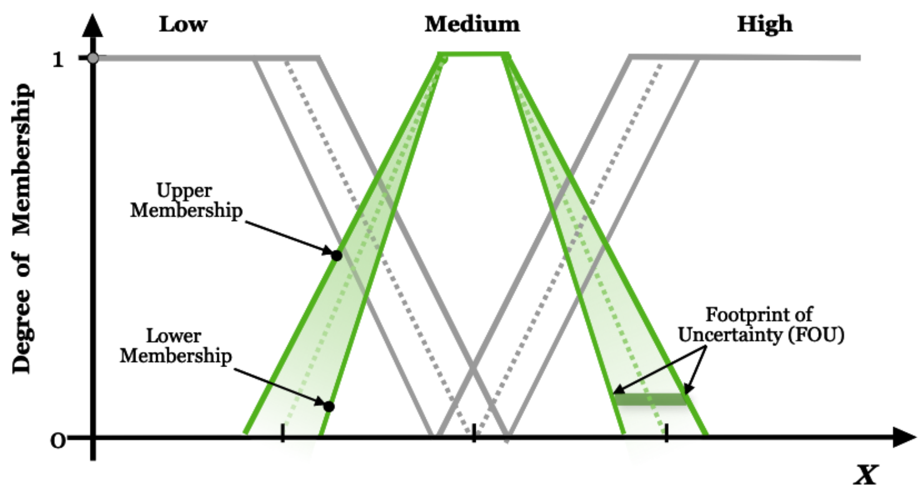

Figure 3.2. A type-2 fuzzy set (Source: [57])

Generally, any type-1 fuzzy set can be extended to its corresponding type-2 fuzzy set. Thinking of a collection of embedded type-2 fuzzy sets provides a better representation to understand how a type-2 fuzzy set $\tilde{A}$ resembles [57]. To better demonstrate this concept, Figure 3.3 depicts a Gaussian pattern with its corresponding FOU. As can be observed there are several embedded fuzzy sets contained between the upper and lower membership functions.

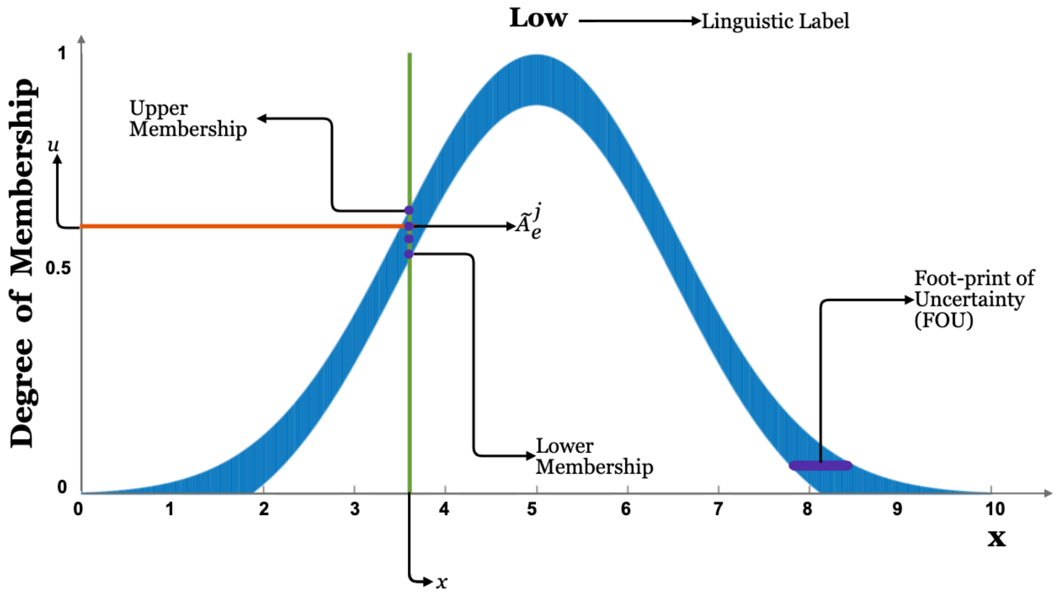

Figure 3.3. FOU of a type-2 fuzzy set, containing several embedded fuzzy sets (Adapted from [54] and [57])

These concepts can be expressed in Equation 3.4. Where, according to Mendel and John [59], when the universes of discourse X and U are discrete, an embedded type-2 fuzzy set $\tilde{A}_e$ has N elements, where $\tilde{A}_e$ contains exactly one element from $J_{x_1}, J_{x_2}, \dots, J_{x_N}$, namely $u_1, u_2, \dots, u_N$, each with its associated secondary grade, namely $f_{x_1}(u_1), f_{x_2}(u_2), \dots, f_{x_N}(u_N)$, i.e.:

$$\tilde{A}_e = \sum_{i=1}^{N} \left[f_{x_i}(u_i)/u_i \right]/x_i \quad u_i \in J_{x_i} \subseteq U = [0,1] \tag{3.4}$$

Then type-2 fuzzy set $\tilde{A}_e$ is embedded in $\tilde{A}$, and $\tilde{A}$ can be represented as the union of its embedded type-2 fuzzy sets, i.e.:

$$\tilde{A} = \sum_{j=1}^{n} \tilde{A}_e^j \tag{3.5}$$

where n is denoted by:

$$n \equiv \prod_{i=1}^{N} M_i \tag{3.6}$$

where M_i is the cardinality of J_{x_i} [60]. Note that opposite to discrete type-2 fuzzy sets, in continuous type-2 fuzzy sets, there is an uncountable number of embedded type-2 sets, which, is not useful in practical applications [59].

3.1.2.1 Interval type-2 fuzzy logic sets

An interval type-2 fuzzy set (IT2 FS) can be seen as a fuzzy set that incorporates an uncountable number of embedded type-1 fuzzy sets. An IT2 FS can be characterised as follows [57]:

$$\tilde{A} = \int_{x\in X}\left[\int_{u\in J_x} 1/u\right]/x\,, \quad J_x \subseteq [0,1] \tag{3.7}$$

where $\tilde{A}$ is an IT2 FS and all its secondary grades equal 1, x is the primary variable with domain X, u is the secondary variable with the domain J_x at each $x \in X$; J_x denotes the primary membership of x and is defined as follows [57]:

$$J_x = \left\{(x,u): u \in \left[\underline{\mu}_{\tilde{A}}(x),\ \overline{\mu}_{\tilde{A}}(x)\right]\right\} \tag{3.8}$$

An IT2 FS $\tilde{A}$ can be described adequately by its corresponding upper and lower MFs, $\overline{\mu}_{\tilde{A}}(x)$ and $\underline{\mu}_{\tilde{A}}(x)$, respectively. Moreover, the uncertainty incorporated in an IT2 FS $\tilde{A}$ can be obtained from the union of all primary memberships. This union is known as the *footprint of uncertainty* (FOU) of $\tilde{A}$. Therefore, the FOU of an IT2 FS can be described in terms of these MFs as follows [61]:

$$FOU\,(\tilde{A}) = \cup_{x \in X} \left[\underline{\mu}_{\tilde{A}}(x),\ \overline{\mu}_{\tilde{A}}(x)\right] \tag{3.9}$$

Figure 3.4 depicts the main elements of an IT2 FS, where the upper and lower membership functions are two type-1 MFs. These upper and lower membership functions bound the FOU. The upper limit is associated with the corresponding upper membership and it is denoted as $\overline{\mu}_{\tilde{A}}(x)$, $\forall x \in X$, i.e. [61]:

$$\overline{\mu}_{\tilde{A}}(x) \equiv \overline{FOU\,(\tilde{A})} \quad \forall x \in X \tag{3.10}$$

Similarly, the lower limit is associated with the corresponding lower membership and it is denoted as $\underline{\mu}_{\tilde{A}}(x)$, $\forall x \in X$, i.e. [61]:

$$\underline{\mu}_{\tilde{A}}(x) \equiv \underline{FOU\,(\tilde{A})} \quad \forall x \in X \tag{3.11}$$

As can be observed the additional degree of freedom of an IT2 FS is represented by the third dimension. This third dimension represents the secondary membership function at a given observation x'.

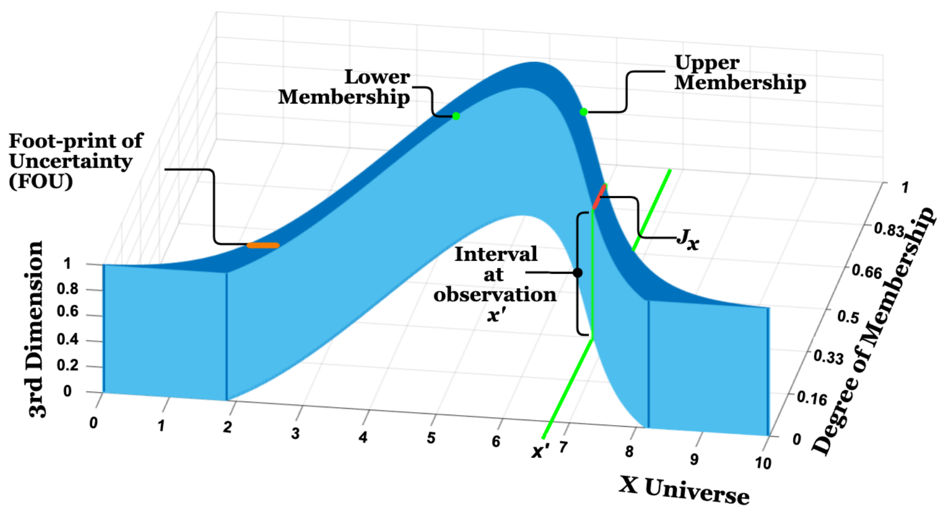

Figure 3.4. An IT2 FS and its main elements (Source: [61])

3.1.2.2 General type-2 fuzzy logic sets

To better understand the role of general type-2 fuzzy sets, it is worth recapitulating that in type-1 FSs there is no uncertainty associated with the primary membership value at which the second grade is 1 [62]. In the other hand, in IT2 FSs the uncertainty is equally spread in the third dimension; therefore, the maximum uncertainty is always reached in the interval at a given observation x', which has an associated secondary membership of always 1 [62]. As can be observed, by employing type-1 FSs and IT2 FSs it is not possible to handle uncertainty in the third dimension in a precise manner. As a result, general type-2 fuzzy sets (GT2 FSs) address this shortcoming by facilitating the modelling of uncertainty within any degree between type-1 and IT2 fuzzy sets [62]. Figure 3.5 offers a comparison among type-1 FS, IT2 and GT2 fuzzy sets. Where the highlighted region illustrates the capabilities for modelling uncertainty in each of the depicted fuzzy sets.

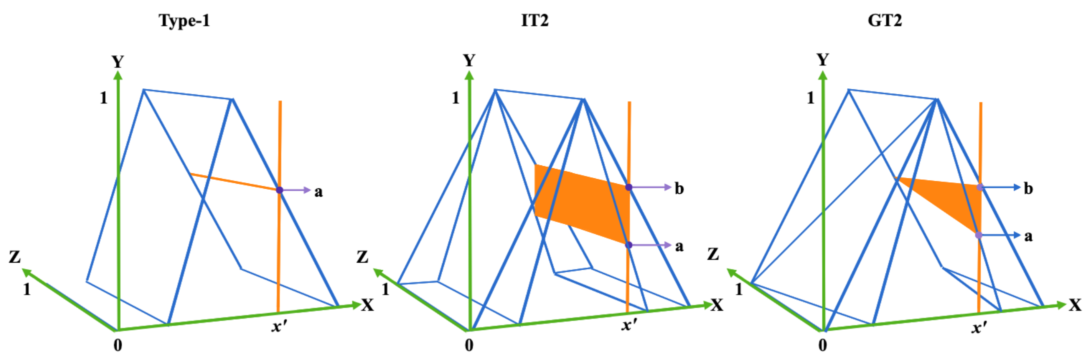

Figure 3.5. Comparison among type-1, IT2 and GT2 fuzzy sets (Source: [62])

Formally, a GT2 FS $\tilde{G}$ can be defined as follows [57]:

$$\tilde{G} = \int_{x \in X} \int_{u \in J_X} \mu_{\tilde{G}}(x,u)/(x,u) \tag{3.12}$$

where $0 \leq \mu_{\tilde{G}}(x,u) \leq 1$, and the integral denotes union over all admissible x and u.

The next section describes the different types of fuzzy logic systems (FLSs) from two perspectives. The former refers to type o fuzzy set being employed, and the latter refers to the source of the knowledge used in its construction.

3.2 Types of fuzzy logic systems

The literature points out two general definitions of fuzzy logic systems. The first one states that if the inputs or outputs in a system are modelled as fuzzy sets then a fuzzy logic system (FLS) has been conceived [56]. The second one mentions that a FLS refers to a nonlinear mapping of an input data vector into an output data vector [57].

A FLS can be categorised according to two main criteria. First, according to the type of fuzzy sets that are based on. Second, the source from where the knowledge is collected from, these are mainly experts and data [54]. The following subsections are devoted to describing these types.

3.2.1 Type-1 fuzzy logic systems

Generally, a FLS follows a rule-based approach. A FLS aims to map the inputs into outputs via the fuzzy reasoning that is encoded in the rules [57]. Figure 3.6 depicts the main components of a type-1 FLS; these are fuzzifier, rules, inference engine and defuzzifier [57].

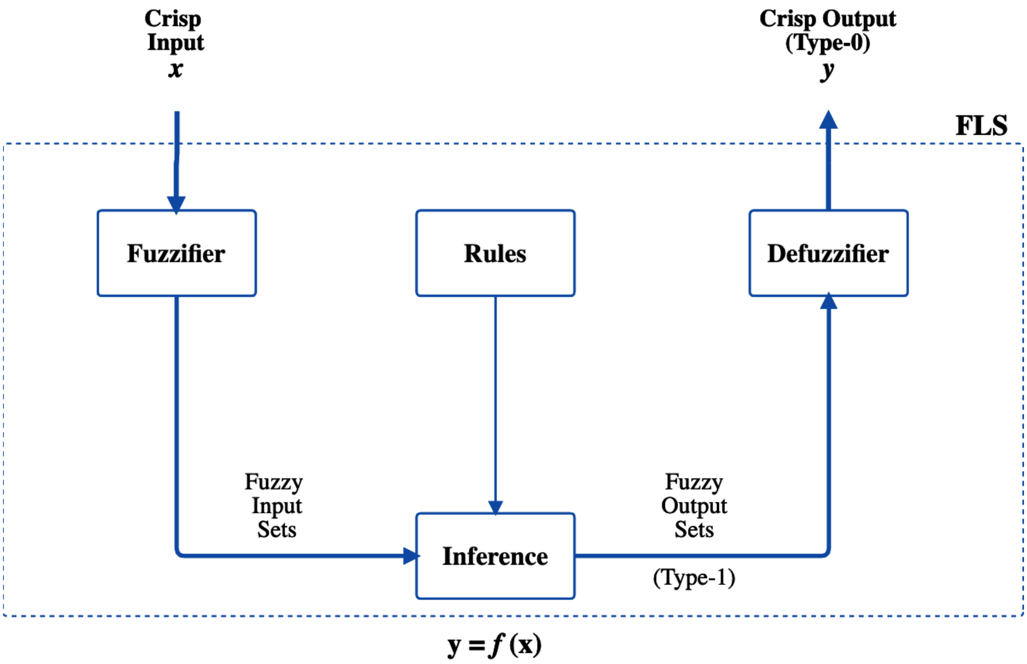

Figure 3.6. Type-1 FLS (Source: [57])

These components can be described as follows:

- The *fuzzifier* aims to map the crisp inputs into fuzzy input [63]. Generally, two types of fuzzifier interfaces can be found. These are singleton and non-singleton fuzzifiers [64].
- A *rule* is a mechanism to generate a programmatic response to a set of conditions, composed of two-part statements. The first part is known as the *antecedent* of the rule. The antecedent focuses on defining the tests for a condition. The second part is known as *consequent* of the rule. The consequent specifies the actions to take when the condition is met [53].
- The fuzzy *inference* engine focuses on combining the fuzzy rules with the mapping from the fuzzy inputs sets to fuzzy outputs sets [57]. In fuzzy

logic, each rule is evaluated by a *fuzzy implication*. A fuzzy implication is a function that evaluates the fulfilment degree of a fuzzy rule [65].

- *Defuzzification* focuses on selecting a single value from a fuzzy set [53]. In type-1 FLS, the defuzzifier produces a crisp output from the type-1 fuzzy output sets inherent in the fuzzy system. Defuzzification methods include maxima, mean-of-maxima, centroid, centre-of-sums, height, modified height, and centre-of-sets among others [57].

3.2.2 Type-2 fuzzy logic systems

The structure of a type-2 FLS share the same components of its type-1 counterpart. However, in the type-2 FLS a type-reduction algorithm precedes the final defuzzification step [54]. Figure 3.7 illustrates the architecture of a type-2 FLS which adds the mentioned step in the block labelled as *type-reducer*. Type reduction is an operation that maps a type-2 fuzzy set into a type-1 fuzzy set [66]. Type reduction methods are an extension of type-1 defuzzification methods [67].

This thesis focuses on an IT2 FLS; therefore, the type-reduced set is also an interval, and it is characterised by the following structure [57]:

$$Y_{TR} = [y_l, y_r] \tag{3.13}$$

The expression for the centre-of-sets type reduction for an IT2 FLS can be generalised as follows [57]:

$$Y_{cos}(x) = Y_{TR} = \int_{y^1\in[y_l^1,y_r^1]} \cdots \int_{y^M\in[y_l^M,y_r^M]} \int_{f^1\in\left[\underline{f}^1,\overline{f}^1\right]} \cdots \int_{f^M\in\left[\underline{f}^M,\overline{f}^M\right]} \Big/ \frac{\sum_{i=1}^{M} f^i y^i}{\sum_{i=1}^{M} f^i} \tag{3.14}$$

where $Y_{cos}(x)$ is an interval set determined by its left endpoint y_l and its right endpoint y_r, $i = \{1, \dots, M\}$ and Mcorresponds to the total number of rules, f^i denotes the firing strength of the i^{th} rule which is an interval type-1 set determined by its left endpoint $\underline{f}^i$ and its right endpoint $\overline{f}^i$ [68].

Similarly, for defuzzification, this thesis calculates the centroid as [57]:

$$y(x) = \frac{\sum_{l=1}^{\alpha} y_k \mu_Y(y_k)}{\sum_{i=1}^{\alpha} \mu_Y(y_k)} \tag{3.15}$$

Consequently, the crisp output $y(x)$ is the average of the endpoints of the type-reduced set $Y_{cos}(x)$. It can be expressed as follows [57]:

$$y(x) = \frac{y_l + y_r}{2} \tag{3.16}$$

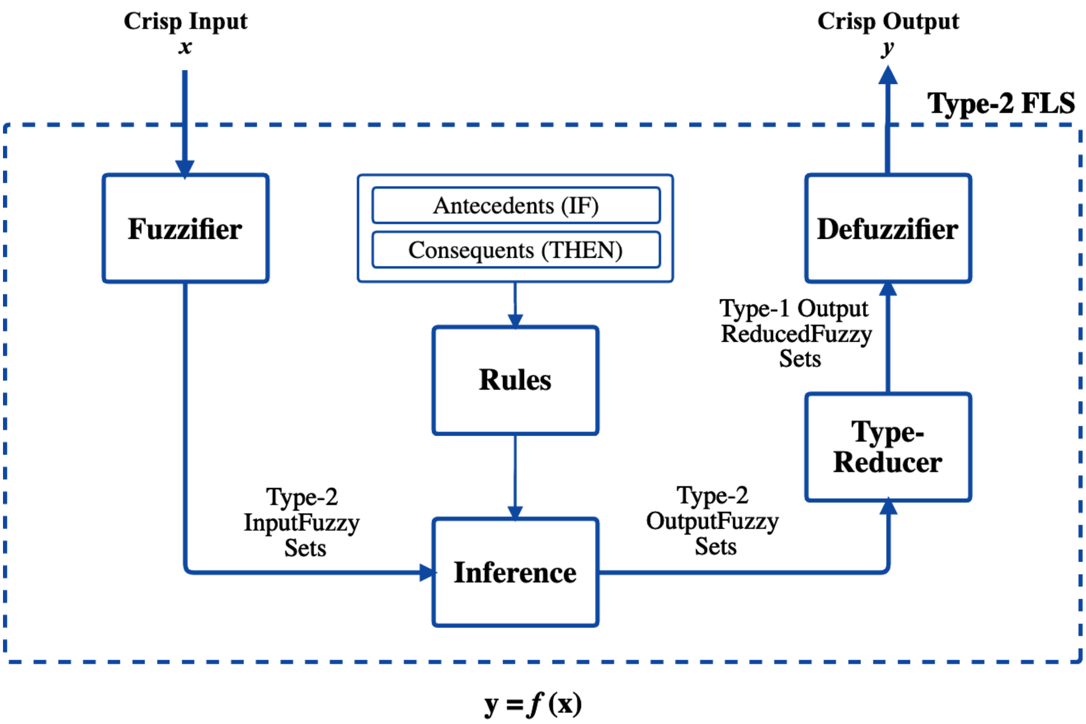

Figure 3.7. Type-2 FLS (Source: [57])

3.2.3 Expert-based fuzzy logic systems

Expert-based fuzzy logic systems collect knowledge from experts. The success of an application depends significantly on the efficiency and quality of *knowledge acquisition*. Therefore, experts' role is vital to identify inputs and outputs, identify crisp and fuzzy variables, formulate the fuzzy rules, assign the importance to each element of the rule base, identify potential constraints and define the expected performance [53], among others.

When building real-world applications, there is not a fully fixed order to design an expert-based fuzzy system. Figure 3.8 provides a non-exhaustive flow of the relevant task involved in their construction, where the simulation model block is highlighted to indicate its relevance as a gateway step for the real use of the fuzzy system being designed.

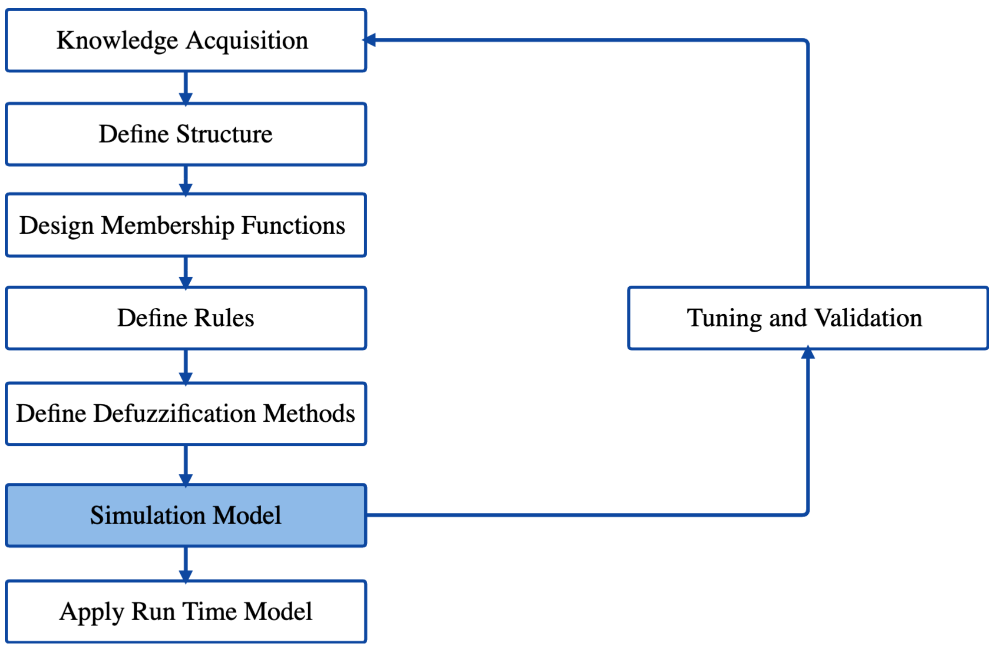

Figure 3.8. Relevant tasks of applying expert-based fuzzy systems (Source: [53])

3.2.4 Data-driven fuzzy logic systems

Data-driven fuzzy logic systems rely on high availability of quality data that reflect the relationship between inputs and outputs. An essential advantage of data-driven fuzzy logic systems is that they reduce the role of experts in defining the system, which is relevant when the access to experts is limited or scarce. Design a data-driven fuzzy system does not have a fully fixed order. However, Figure 3.9 depicts a suggested flow sequence with the relevant task involved in data-driven fuzzy systems [53].

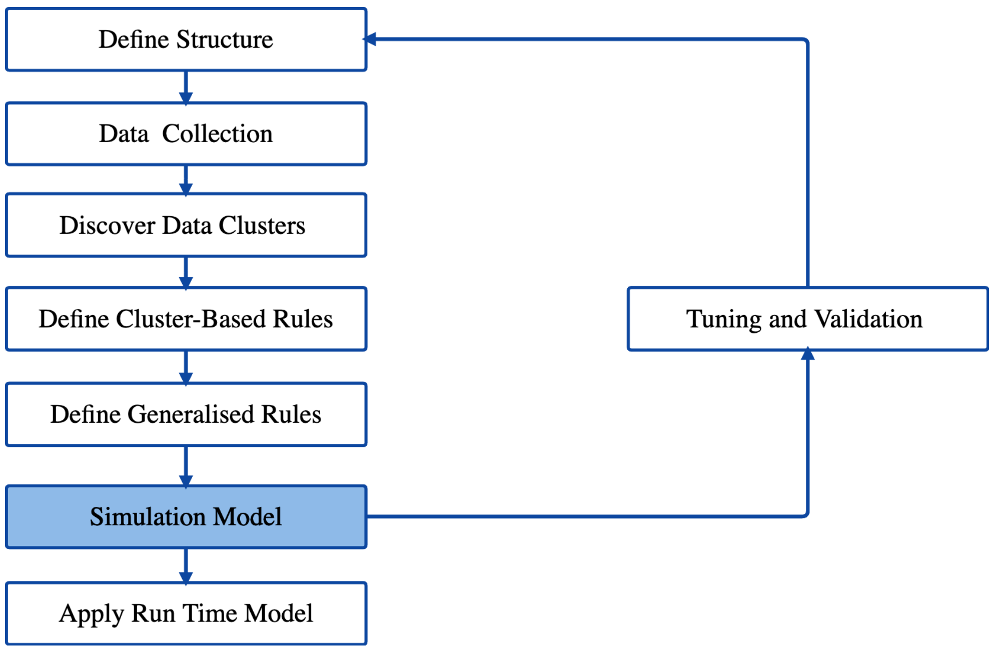

Figure 3.9. Relevant tasks of applying data-driven fuzzy systems (Source: [53])

Data collection is the core of the process; thus, the process behaviour should be represented adequately based on the collected data. Data processing encompasses discovering data clusters and defining the corresponding rules. The generalised rules will reflect the granularity of the fuzzy clusters. In practice, it is beneficial for the support of domain experts. The simulation model block is highlighted to indicate its relevance as a gateway step for the real use of the data-driven fuzzy system being designed.

3.3 Applications of fuzzy logic systems

Application of fuzzy logic systems can be found in a broad spectrum of scenarios. Relevant examples of fuzzy logic systems adoption can be found in areas such as transport systems, industrial process control, and search engines.

In transport systems, fuzzy logic systems implemented predictive controllers based on fuzzy sets by modelling features such as safety, comfort, energy savings, speed, elapsed time, and stopping precision [69]. In industrial process control, fuzzy logic enabled monitoring, operation communication, and reporting [70]. Finally, fuzzy logic is contributing to the evolution of search engines into question-answer systems [71].

3.4 Discussion

This chapter has provided an overview of the concept of fuzzy logic including the foundations of fuzzy sets theory and the types of fuzzy sets (T1, IT2, GT2). Moreover, this chapter reviewed types of fuzzy logic systems based on the type of fuzzy sets employed for their construction. Additionally, it provided detailed insight of the functionality of their core operating elements, and it presented a brief review of the type of fuzzy systems based on the source of the knowledge employed for their design. Finally, this chapter mentioned some of the applications that have potentiated the fuzzy logic adoption across relevant domain applications.

Each section of this chapter has focused on providing the foundations and advances that have positioned fuzzy logic theory as a preference among researchers and practitioners to build real-life applications. In summary, model representation of human thinking is a unique feature found in fuzzy logic. This characteristic has benefited a wide variety of domain applications and the adoption of fuzzy logic has been gaining a wider audience gradually. Moreover, type-2 fuzzy logic is capable of including uncertainty by incorporating an additional degree of fuzziness. Notably, the introduction of the concept of type-reduction helped to define type-2 fuzzy logic system architectures fully.

Certainly, at its early adoption, FL demonstrated its value in control applications. However, over the last 15 years numerous research efforts have shown that it is possible to capture the variation in human decision making using IT2 FLSs [72]. Consequently, as mentioned in Section 3.3, FL has gone beyond control automation and positioned itself as a suitable tool to solve problems in domains such as transport systems, industrial process control, and search engines.

This thesis is based on the IT2 FL foundations. Therefore, the framework presented in this proposal focuses on developing an IT2 FLS based GDS for optimising field service delivery in the telecommunications industry, while providing a sensible approach for some challenges that FL techniques face in real-world applications. Namely, the *low complexity* commonly found in fuzzy systems that are limited a to certain number of rules.

The proposed framework allows the treatment of an exponential number of rules while also provides the mechanism to rule base optimisation. Another related challenge refers to the *difficulty to scale-up*; for example, a membership function representing the term for *high* demand may have a different meaning in two geographical locations. The proposed framework solves this by the incorporation of an optimisation algorithm, namely the Big Bang-Big Crunch (BB-BC) algorithm, reviewed in Section 9.1.

Moreover, the challenge of the *high cost of maintenance* which manifests when even minor changes in any component of the system may require full redesign is addressed by the proposed framework by incorporating an update mechanism that monitors and maintains the system at an optimal operational state.

Notably, the aim is to support human decision making in a highly competitive and unstable environment, which characterise the current global markets. While intelligent tools may unveil exceptional opportunities for value creation, there is a fundamental problem to address, i.e. transparency in the methods that augment and extend human capabilities. This thesis presents an attempt to reduce the gap for this need while maximising the type-2 fuzzy logic potential to provide human thinking model representation.

The next chapter will introduce the concept of explainable AI (XAI). Moreover, it will provide a brief overview of explainable techniques, including intrinsic, post-hoc, global, local, model-specific and model-agnostic models, and it will review the role of decision-making support systems in the industry.

Finally, it will discuss the role of FL for human-understanding of problem solving.

Chapter 4 - Explainable AI for Humans

The increasing number of tools powered by *Artificial Intelligence* (AI) is not exclusive to consumer applications. Companies across industries are investing significantly to benefit better at harnessing the capabilities of AI. As a result, intelligent solutions are being adopted in all sectors of the economy. Notably, these intelligent solutions are being placed at the core of business operations [73].

The term AI refers to a field that studies aspects of intelligence concerning the ability of learning, make decisions and solve problems [74] through computers algorithms and machines [75]. AI encompasses modern *machine learning* (ML) techniques, search methods, statistical techniques and approaches based on observed behaviour [76].

A research field known as *Explainable AI* (XAI) has emerged to enable achieving more transparency within AI models and solutions. This chapter will provide a brief overview of XAI and the main explainable techniques commonly employed. Successively, it will review the role of decision-making support systems powered by AI in the industry. Finally, this chapter will discuss the role of Fuzzy Logic for human-understandable problem-solving.

4.1 Overview of Explainable AI

XAI aims to facilitate a more transparent AI [77]. Consequently, decision-making instruments under the XAI paradigm may be easier to understand by individuals that are not necessarily experts in that particular problem. Moreover, such mechanisms aim to accelerate trust gain. As AI solutions are taking part in more aspects of human activity, there is a real need of knowing when to trust AI applications (when AI tools could fail? when could they succeed?) and to understand why or why not a decision was made.

Currently, a large variety of AI models cover a wide range of domain applications. As a result, there are several XAI approaches with variations in the terms (e.g. interpretable, explainable, understandable, transparent). However, the overall aim remains, i.e. to deploy more transparent AI models that can be understood by humans. In this regard, the Defense Advanced Research Projects Agency (DARPA) outlines primarily three models to deploy XAI solutions: Deep explanation, Interpretable Models and Model Induction [78].

The aforementioned methods are neither mutually exclusive nor exhaustive. However, this classification can be a useful guide to review its features. The following subsection will provide a brief review of these methods.

4.2 Explainability strategies

Beyond the many differences in the perception of explainability, the ultimate goal is to make intelligent models that are human-like understandable. The different explainability strategies currently available in the literature are briefly described below.

Deep Explanation refers to the study of deep learning capability to learn explainable features. These models implement neural networks with more extensive parameters and layers modelled in one of the following network architectures: unsupervised pre-trained networks, convolutional neural networks, recurrent neural networks and recursive neural networks [79].

Interpretable Models focus on the learning structures, interpretability and causality of the models; these models can be global or local. *Global interpretability* focusses on understanding the end-to-end logic of a model, i.e. from the relationship among the input variables to the entire reasoning leading to all the different outcomes [80]. *Local interpretability* focuses on explaining the reasons for a specific outcome. A non-exhaustive list of interpretability techniques includes: *gradient analysis* [81]; *model decomposition* [82]; *meaningful perturbations* [83]; *saliency detection* [84]; *propagating activation differences*, [85]; and *unified frameworks* [86].

Model Induction focuses on inferring an explainable model from two angles; the first refers to interpretability that can be applied to any model defined as a black box; this is known as *model agnostic* [77]. The second refers to interpretability that is applicable only for a particular type of model; this is known as *model-specific* [77]. *Model-specific interpretability* is limited to intrinsic algorithms [87]. Therefore, this type of interpretability is conditioned to simple structures such as decision trees [88] and linear models [89]. *Model-agnostic interpretability* separates prediction from explanation, and it is generally applied after the prediction is complete, i.e. post hoc. Mainly four techniques are employed in model-agnostic interpretability. Namely, *visualisation* [90], [91] and [92]; *knowledge extraction* [93], [82], [94] and [95]; *influence methods* [96], [97], [98] and [99]; and *example-based explanation* [100] and [101].

4.3 Relevant challenges for explainability

Beyond the many differences in the perception of explainability, the ultimate goal is to make intelligent models that are human-like understandable. Generally, a model with more embedded complexity will face more difficulties for its explanation and interpretation [77]. The techniques mentioned above have uncovered numerous challenges that need to be solved to succeed in providing human-like explainability to both experts and non-experts users.

For example, deep learning models need to incorporate human knowledge into their construction; therefore, humans will be more familiar with hybrid knowledge representation. Moreover, deep learning models need support from progressive visual analytics; therefore, users will be part of the analysis loop rather than just reviewing the results of the predictions or revising the training process, which commonly is offline after the training process is complete [102].

Additionally, local and global interpretability models have been developed with the main focus of solving image classification problems. Consequently, applying them to other domain application may require more investigation for achieving successful explainability. Hence, the need for other approaches applicable to different types of models. The next subsection will provide a brief review of AI-based solutions in the industry.

4.4 AI-based decision support systems in the industry

Augmenting human capabilities to decision making and problem-solving in core business processes is vital for competitive advantage across industries. Currently, AI is seen as a mechanism to achieve this augmentation. AI applicability can vary significantly across industries. However, AI adoption in core business processes has already begun. In a recent review of the status and development of AI [103], it is pointed out that AI will bring 14% growth to global GDP by 2030.

The current popularity around AI is the result of the convergence of algorithmic advances, improvement of sensors, data proliferation, increase in storage and computing power, among others [104]. However, the efforts to deploy technologies that enable AI to solve real-world problems have a history of almost 70 years. During this period, the popularity and adaptation of AI solutions have been unsteady. Figure 4.1 depicts the booms and the slowdowns in the AI trajectory. As can be observed, the AI field has faced collapses in the perception of its value creation. These collapses are commonly referred to as AI winters [198].

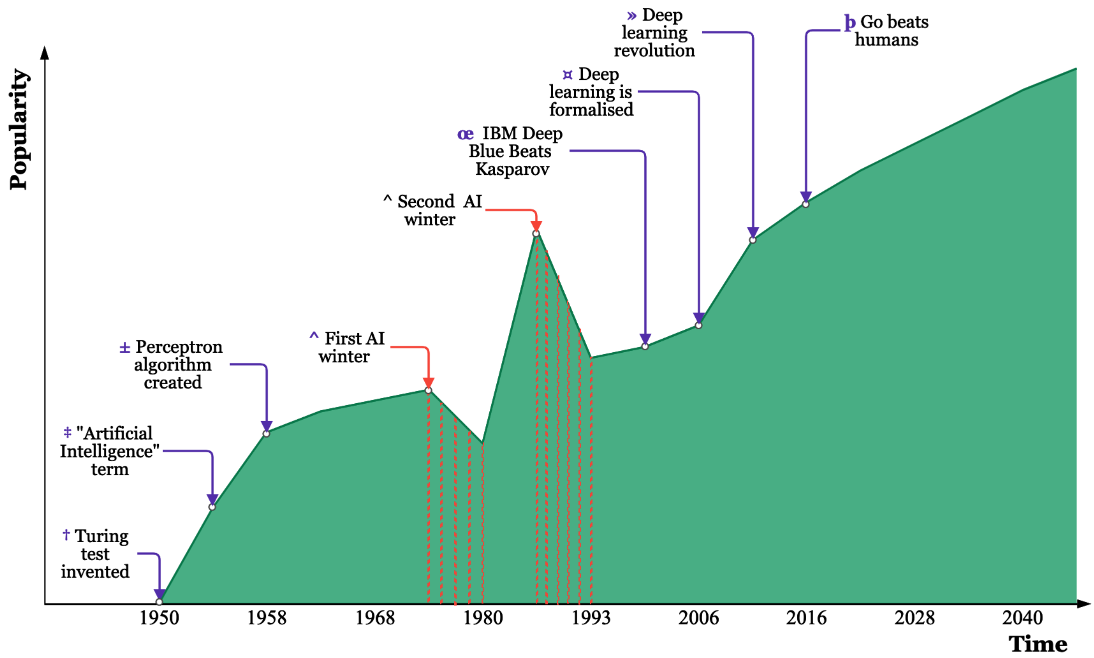

Figure 4.1. Booms and slowdowns in artificial intelligence (Sources: † [105], ‡ [74], ± [106], ^ [107], œ [108], ¤ [109], » [104], and þ [110])

Since 1996, research papers, private equity investment, AI start-ups and AI tools for the industry have proliferated [103]. However, as the importance of the application increases, the expectations for flawless and reliable AI solutions increase. Consequently, researchers and practitioners agree on factors influencing the acceptance and adoption of AI-based solutions. These factors include transparency, explainability and interpretability [104]. Table 4.1 summarises the key differences among these factors, which can be briefly described as follows:

Transparency — This refers to the possibility to visualise the process chain [104]. Transparency allows knowing the data that the algorithm uses, the architecture of the AI solution, and the type of data processing, among others.

Explainability — This refers to releasing the knowledge about how the outcomes of the AI system were obtained [104]. Explainability focuses on making the underlying reasoning explicit by highlighting which inputs led to a particular conclusion. Explainability allows humans to understand how the system works, its limitations and its potentials.

Interpretability — This focuses on revealing how AI solutions work and how they learn [104]. Humans benefit from interpretability by understanding how the system works without the need to know the reasons behind the scenes [100].

Table 4.1– Key factors and their focus for AI acceptance (Source: [104]).

Factor	Focus	Answer to
Transparency	- Overall data - AI system architecture - Type of data processing	- What is inside the AI solution?
Explainability	- Inputs of influence - Reasons	- What inputs the AI solution uses to give a specific outcome?
Interpretability	- Learning process - Process operation	- How does the AI system work?

Additionally, new legislation is emerging in an attempt to regulate when things go wrong concerning AI-based technologies. For example, the European Commission has created different liability directives regarding emerging digital technologies, such as the Internet of Things (IoT), Artificial Intelligence, advanced robotics and autonomous systems [111]. However, liability is an active research topic, and further advances will be observed in the immediate future.

Finally, other laws outline the rights and obligations of the use of automated decision making. For example, in Europe, the General Data Protection Regulation (GDPR) request that meaningful data and explanation must be provided [112]. Another concern refers to the ethics around artificial decision-making processes. Hence, ethics is another research direction for the efficient adoption of AI solutions in the industry.

The development of a comprehensive XAI framework is required for boosting confidence in products and services powered by AI. The following section reviews the role of fuzzy logic for human-understandable problem-solving.

4.5 Fuzzy logic for human-understandable problem-solving

As transparency in AI-based models increases, more intelligent solutions will be rolled out by industries and governments [76]. In addition to the factors described in the previous section, it is essential to remember that the ultimate goal is that AI systems can be understood by humans. Fuzzy logic aims to provide human-understandable problem-solving by mimicking how humans think. Human thinking is a complex process thoroughly studied by diverse fields such as psychology, neuroscience and artificial intelligence. Problem-solving represents a higher level of thinking, including judgment, reasoning and decision making [113].

In practice, human thinking lacks the precision of mathematics, and it carries out its processes with approximations rather than with precise data.

Perception is particular for a person or a group of people. For example, rather than saying 60 miles per hour, 5% of battery life, 95 decibels or 35 thousand dollars; a person probably will say the speed is quite fast, the battery has a low charge, the sound is very loud, and the salary is a high income, respectively.

Fuzzy logic helps to represent this imprecision by modelling and creating a set of if-*then* rules to describe a given behaviour in human-readable form. A trivial example of this form could be: “if the sound is very loud and it is very late in the neighbourhood then turn the volume down”.

Chapter 3 provided a detailed description of fuzzy logic and its capabilities. This thesis develops an intelligent tool based on fuzzy logic’s principles. What is more important to consider in this section is that the linguistic labels employed in fuzzy logic systems support modelling the uncertainty naturally present in the information. Similarly, the generated rules can be read by any human because they are written in the same language as humans use in everyday life. The more understanding the user has about an AI-based solution, the sense of trust, transparency, explainability and transparency increases. Hence, an intelligent solution powered by fuzzy logic can offer a sensible way to achieve XAI for humans.

4.6 Discussion

This chapter has provided an overview of explainable AI for humans by reviewing some of the common XAI strategies. Subsequently, it introduced the role of AI-based decision support systems in the industry and the main characteristics that will enable a wider AI adoption. Finally, this chapter presented the role of fuzzy logic for human-understandable problem-solving, which is the approach implemented in this thesis.

Each section of this chapter was devoted to providing insight into the advances and characteristics that define the XAI field. To recapitulate, the adoption of AI-based solutions is occurring primarily in core areas of business activities across various industries. Notably, the telecom sector, with its service operations functions, is leading the overall adoption of AI tools. It is noteworthy to point out that this thesis focuses on these two important economic drivers. Moreover, AI solutions must incorporate the ability to explain the underlying algorithms that power their final decisions to humans. Hence, the XAI field outlines the strategies and characteristics to deploy more transparent AI solutions that can be understood by humans. Advances in the XAI field include a set of strategies to achieve its aim. These strategies are neither mutually exclusive nor exhaustive. Figure 4.2 attempts to summarise these techniques in a pseudo taxonomy of XAI methods.

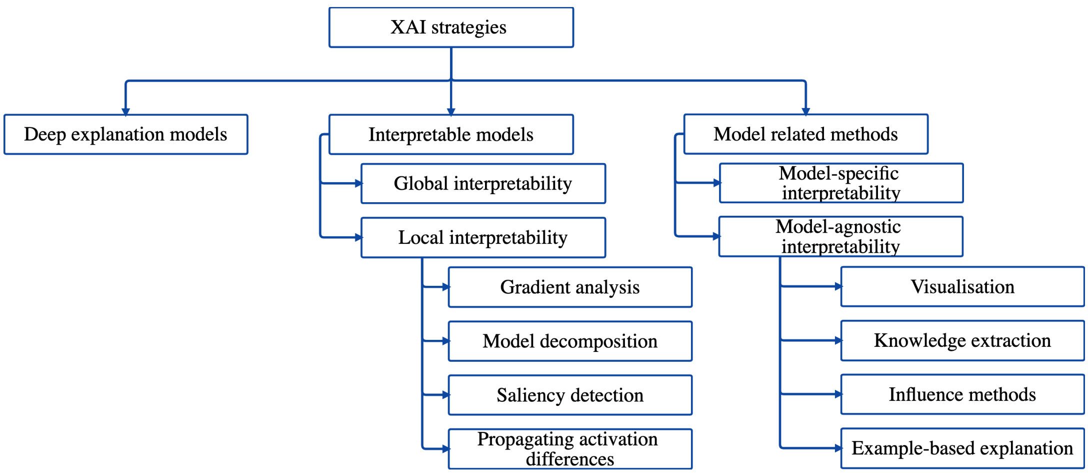

Figure 4.2. Pseudo taxonomy of XAI methods (Source: [77])

Notably, fuzzy logic capabilities enable the representation of human thinking imprecision by modelling and creating a set of *if-then* rules to describe a given behaviour. These rules can be read by humans because they are written in their language. It is worth clarifying that the *if-then* rules capability is not exclusive of fuzzy logic systems. This feature is also available in other white-box approaches. However, complex systems often cannot be easily understood and analysed by non-expert users. Some examples can be briefly reported as follows.

The system developed in [114] generates *if-then* rules; however, these statements are chained in long "*if-then … else-if…else*" structures. It can be anticipated that this reduces interpretability. Furthermore, the tool developed in [115] helps non-expert to understand classifiers by navigating and verifying the rules and their effect in the black-box model. The maximum of rules was 60 with 20 features. However, this approach uses precise boundaries in the antecedents and consequents of the rules. Moreover, the problem is theoretical rather than real-world related; therefore, the tool cannot easily handle the inherent uncertainty present in real-world problems.

Additionally, it is worth clarifying that the uncertainty handling capability of fuzzy logic has already been employed to deploy XAI systems. For example, the work presented in [116] considers different aspects of interpretability concerning hierarchical fuzzy systems. Additionally, the model developed in [117] contributes to explainability based on learning relevant relations and properties in a dataset. However, these approaches were not designed to handle cases where a sparse rule base does not cover the whole research space. Therefore, there is a need for further exploration of fuzzy logic approaches to enhance explainable models by employing optimised fuzzy logic systems. Hence, the relevance of the work presented in this thesis.

The next chapter will introduce the concept of computer simulation and its types. Subsequently, it will review the characteristics of *"what-if?"* and *"how-to"* scenarios and outline their contrasts. Moreover, it will introduce the concept of GDS and its role in the field service operations domain to finalise with a discussion on the concept of simulation scalability.

Chapter 5 - Goal-Driven Simulation in Field Service Operations

Saturated markets and fierce competition were the drivers of change in various industries during the past decades. Companies prioritised improvement efforts in various aspects, including operational efficiencies, customer service satisfaction, new markets development and innovative products. Subsequently, in order to achieve these aims, organisations embarked upon an era of digital transformation. As a result, companies' business models and processes became mostly digital, often powered by sophisticated automation technologies.

At present, the number of organisations that have completed the journey mentioned above is higher than those that have not. As a result, an emerging epic disruption is a reality, namely the post-digital era [118]. In the post-digital era, digital saturation is the norm, and automated processes are embedded at the core of the operations, impacting customer expectations and risks across industries. Consequently, companies must include in their operations a strategy to leverage target-oriented approaches to gain a competitive advantage.

This chapter delves into the elements of computer simulation and its applicability in the field service domain. Then, it defines GDS and its relevance in field service operations. Finally, it introduces the term *simulation scalability*, which enables comparisons between systems based on practical quantifiable simulation elements instead of their relative performance.

5.1 Simulation Scenarios

Decision making can benefit from computer simulation through insight obtained from the analysis of various simulation scenarios [119]. A *simulation scenario* can be defined as the possibility resulting from a specific set of conditions and configurations [119]. Typically, a set of inputs are fed into the model; then, these inputs will generate specific outputs accordingly to those conditions. To achieve sensible results from computer simulation approaches, an exhaustive analysis of multiple scenarios is essential; this is known as scenario analysis.

Primarily, *scenario analysis* can be described as the process of reflecting possible outcomes into possible decisions [120]. Scenario analysis is driven by the scenario's proximity to real conditions, the known inputs, the generated outputs and the expected targets. Traditional scenario analysis implies the study of "what-if?" scenarios.

5.1.1 "What-if?" Scenarios

"What-if?" scenario analysis determines the effect of variations in the inputs on the generated outputs [3]. Its general form can be expressed as $Y = F(\Delta X)$,

where Y are the outputs, ΔX are the changes in the inputs and F is the process responsible for transforming the inputs into outputs [3]. For this example, the *"What-if?"* analogy refers to *What-if* X increases/reduces*?* Consequently, the modeller expects to know what effect this change will have on Y? However, real-world applications have a large number of parameters, often with inherent complexities. Hence, the emphasis on studying the effect of even small perturbations in parameters.

Computational and mathematical methods can assist in the study of variances in the parameters and their effect on the generated outputs based on sensitivity analysis techniques [121]. Mainly, in *sensitivity analysis*, the inputs, the simulation scenario and the outputs are exposed to different sources of uncertainty [121]. As a result, sensitivity analysis determines the quality of the simulation model by revealing two essential properties. These are the stability and sensitivity of the simulation model.

For complex models, which is the case for most real-world applications, some *challenges* of "what-if?" scenarios can be described as follows. First, in order to achieve specific desired targets, users need to execute adjustment of inputs by trial and error until the goal is achieved [122]. Commonly, the users of simulation models are expert users or operational planners that might not have the full background of the model; therefore, their cognitive overload can be significant. Second, "what-if" approaches might require substantial computing times [122] due to the architectural flow that "what-if" scenarios follow. In this flow, first, a parameter of a set of parameters is adjusted, then a process takes time to be completed, then the outputs are ready. This flow implies upfront compute-time costs that users need to cover even before obtaining any result. Third, there is the possibility of not finding the adequate input configuration due to a dependency on user expertise and time [122]. Consequently, all the time and resources can result in an unproductive balance.

5.1.2 "How-to?" Scenarios

"How-to?" scenario analysis starts with setting a goal to be achieved under certain conditions embedded into the simulation model [123]. Subsequently, "how-to?" scenario analysis determines a set of actions that allow reaching this goal [123], a target-oriented approach.

In practice, many business decisions are made based on this target-oriented manner rather than on trial-and-error approaches [124]. To better understand the differences between these methods, Figure 5.1 depicts the overall workflow between "what-if?" and "how-to?" approaches. As can be observed, the additional verification in the "what-if?" approach results in increased time and resources. On the contrary, in the "how-to?" approach, the result represents the actions to take for reaching the goal. These actions take the form of the adequate input configuration that delivers the desired goal; hence, its run time advantage when comparing with its counterpart. Additionally, in "what-if?" scenarios, the result is an estimate reflecting the changes in the inputs. Moreover, the result does not reflect any optimisation effect. On the other hand, "how-to?" approaches incorporate the effect of optimisation into the generated results.

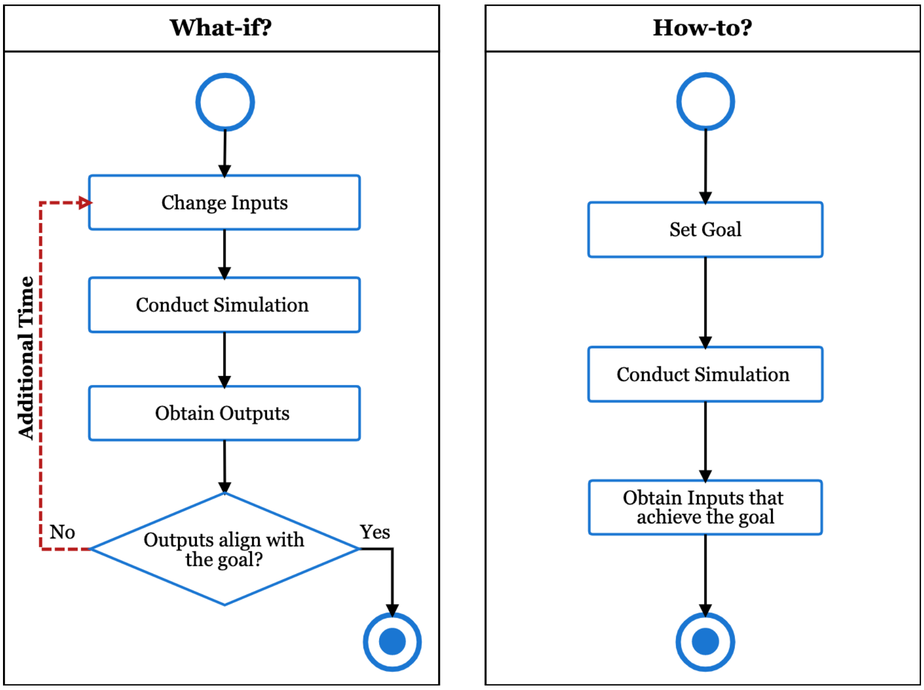

Figure 5.1. Flow comparison between "what-if?" and "how-to?" approaches (Sources: [3] and [123])

Furthermore, in the "what-if?" approach, improving the inputs might require specific expert knowledge, which might not be immediately available. On the contrary, in "how-to?" scenarios, the generation of actions already incorporate expert knowledge previously modelled and maintained in a knowledge base. Finally, all these differences added up to the complexity of real-world problems are better addressed by "how-to?" methodologies due to the noticeable run time benefit.

5.2 Goal-Driven Simulation

GDS aids *"how-to?"* scenarios by searching for the inputs that produce the desired goals [123]. Goals are the expected target values for the performance indicators that the simulation study generates. Adequate data modelling and knowledge representation techniques enable efficient search capabilities. Consequently, GDS attempts to provide the most suitable configuration for the returned set of inputs, which fulfil the desired target.

In GDS, the data fed into the model carry considerable weight with the generated results [125]. Consequently, GDS is restricted by the knowledge derived from these data. Generally, GDS evaluates multiple alternatives over wide search spaces by employing intelligent computational techniques, which incorporate analysis and optimisation capabilities aligned with the desired targets.

The benefits of GDS can be summarised as follows. First, human interaction during simulation analysis is minimised [123] due to the reduction of additional time-consuming validations. Second, as a result of the previous point, human error is reduced [123]. Third, the formulation of “how-to?” questions are more focused-oriented concerning the desired targets in comparison with “what-if?” questions, which are more oriented to explore the system’s behaviour [123]. Finally, since in-depth technical knowledge is not required, GDS allows non-expert users to interact with the simulation model and yet to obtain sensible results.

GDS has evolved into a feasible and robust solution for supporting decision making based on simulation. During the past years, advances in GDS included object-oriented simulation languages [126], knowledge bases powered by artificial intelligence [127], enhanced algorithms for target value search [125], and GDS integration with artificial neural networks [128].

Recently, in [129] and [130], GDS was combined with deep learning models to understand the sensory cortex.

Research challenges in GDS include the availability of an integral framework fully interconnected, efficient knowledge management, accountable learning capabilities, effective uncertainty handling, and multi-purpose and multi-domain application, among others. The next section will introduce the role of GDS to support the decision-making process in the industry.

5.3 GDS in field service operations

Efficient execution and management of field service operation represent one of the main elements that drive companies' cost-effective advantages [6]. Failing at its execution compromises companies' service delivery. As a result, in the worst-case scenario, the permanence of the business in competitive markets can be jeopardised. Broadly, field service operations involve activities such as the detection of a field service need (via physical inspection, remote monitoring, or a customer reporting a fault), dispatching parts and information to the field opportunely, and support of field technician interactions, including field technician scheduling and optimisation [131], which involves solving task allocation concerning skilled staff [5]. The complexity of real-world operations incorporates factors such as travel dynamics, priorities, skills, work-types, among many others. As a result, field service operation processes are expensive.

Various aspects of this problematic situation in the field services operations domain have been addressed successfully by simulation models. For example, integrating scheduling with dynamic simulation models [132], modelling multi-agent simulation systems [133], studying the significance of data assimilation [134], exploring the influence of two scheduling levels [135], accomplishing desired targets via optimisation [136] and finding preferred service composition on demand [137].

However, most of these solutions presented the following shortcomings. First, they modelled their problems of study in linear forms. Second, they present a lack of evaluation of the importance of the input parameters and their influence on the outcomes. Consequently, the solutions mentioned above were reduced to models under the "what-if?" scenarios paradigm, which brings the challenges described in Section 5.1.

Deploying "how-to?" scenarios" is not trivial. Domain applications for GDS include solving forecasting problems, understanding systems' behaviour and implementing heuristic solutions [138]. For example, in [136], a goal-driven approach was implemented to learn the system dynamics for the best performance for a given task. Additionally, in [137], a goal-driven approach was employed for a self-organizing service model for task resolution and execution in pervasive mobile environments. However, these approaches reduced their respective problems of study to linear and to heuristic distributed backwards-chaining models, respectively.

As a result, the aforementioned solutions did not study the effect of uncertainty naturally inherent on real-world problems. Hence, the relevance of a solution that provides a complete framework fully interconnected, efficient knowledge management, accountable learning capabilities, and effective uncertainty handling, which are the focus of this thesis.

5.4 The need for GDS in BT

BT is one of the world's leading communications services companies. Its core business activities include providing fixed-line services, broadband, mobile, TV products and services and networked IT services [139].

Scheduling algorithms are executed daily to allocate engineers with the right skills to the required jobs. The successful completion of these jobs impacts directly service level performance metrics that contribute to the company's revenue [140]. Moreover, many different factors are involved in the allocation processes. Due to their importance, the prediction of those dynamics is required. The benefit from these predictions is reflected in the capacity for decision-making processes for de-risk investment decisions on the field service operations. GDS is an approach capable of facilitating the environment to analyse and generate such predictions. However, GDS and other technologies must be aligned with the company's purpose, ambition and values.

Unsurprisingly, a key factor for successful operations is to achieve the lowest throughput cost and delivery. To accomplish this, efficient simulation of the field service delivery operations will be critical to analyse scenarios and all different factors before their real-life deployment. A simulation approach aligned to achieve specific targets is vital to speed up this converging process. Hence, the importance and applicability of a GDS approach that is scalable at BT. The next section will introduce the role of scalability in simulation processes.

5.5 Simulation scalability

In the computer simulation context, the term scalability is commonly employed by researchers to assess their simulation models [141]. For example, in a simulation model of the Internet of Things [142], scalability was used to assess the ability of the model to work in larger and highly intensive interacting scenarios. Moreover, scalability was studied in a simulation framework for the solution of partial differential equations [143] by considering performance metrics such as time, flops, and the number of bytes injected into the network. Additionally, scalability in an agent-based simulation approach was interpreted as the capability to simulate hundreds or more agents [144]. Furthermore, in a molecular simulation model [145], scalability was studied concerning the execution time.

However, as can be observed from the examples listed above, the term scalability has a different meaning according to each case. For some, scalability refers to the capability to simulate more entities, see [142] and [144]. For others, scalability refers to a combination of performance metrics, see [143], and for some instances, scalability refers to execution times, see [145]. Hence, the need to define a scalability criterion to evaluate the simulation process that is both quantifiable and meaningful [146].

In the context of this thesis, *scalability for GDS* can be defined as the property that allows the simulation model to be extended in two main aspects: simulation capability and architectural capability [146]. The former is a function of performance metrics, simulation size, performance requirements and scenarios covered. The latter is a function of the performance of every single architectural element of the simulation system. The following chapters will refer to this concept during their development. This subsection aimed to define the criteria that define the concept of scalability for the GDS approach presented in this thesis.

5.6 Discussion

This chapter has introduced the concept of computer simulation and its types. Moreover, it presented the “what-if?” scenario analysis approach and its challenges, and it reviewed the “how-to?” scenario analysis approach and outlined the differences with its “what-if?” counterpart. Then, it defined the term of GDS and its role in the field service operations domain. Successively this chapter presented the case for the need for a GDS approach in BT rather than traditional and preventive approaches. Finally, the chapter defined the scalability criteria for the GDS approach developed in this thesis.

Each section of this chapter has been devoted to providing insight into the role of GDS in the field service operations in the telecom sector within a major TSP, namely BT. To recapitulate, GDS is an approach that facilitates achieving specific goals by providing the configuration of the most suitable inputs, which fulfil the accomplishment of the desired targets. GDS is based on the “how-to?” scenario analysis approach. In contrast with its “what-if?” counterpart, the “how-to?” approach facilitates determining a set of actions that allow reaching specific goals. In simulation problems, this set of actions are commonly translated to a set of input parameters.

In practice, GDS approaches to solve the issues derived from the *trial-and-error* methodology, which is present in traditional approaches such as "what-if?" scenario analysis. Therefore, an integral GDS approach will suit real-world operations better when operating in high demand and volatile environments.

Currently, the advances of intelligent tools have focused on providing optimum outcomes. However, in practice, these optimum outcomes cannot easily be achieved. Often, intelligent solutions predict the best results for the best-case scenario, which results in 100% of success. This is understandable since these solutions were conceived as optimisers. However, in practice, that forecasted 100% of success is commonly missed. Therefore, planners and managers acknowledge the benefit of knowing in advance the possible actions to take given different conditions. These conditions model the scenarios and facilitate the evaluation of different business targets. As a result, GDS enables planners to decide which actions need to be implemented in order to achieve desired business targets that reflect a more accurate representation of field service operations.

In the telecom industry, the efficiency of the field service operations affects various performance metrics that directly impact the profitability of the business. To provide a real-world example of this importance, Figure 5.2 depicts a customer service measure that focuses on meeting the commitments the company makes to customers. These commitments may include keeping to appointment times, completing orders in the promised timeframe or fixing faults when agreed [147]. These tasks directly relate to the field services operations domain, as detailed in Section 2.1.

It is worth to clarify that, as reported in Section 5.2, GDS has been employed in other industries. However, the aforementioned applications do not provide a holistic approach to tackle the main challenges in the GDS deployment, which include the lack of an integral framework fully interconnected, efficient knowledge management, accountable learning capabilities, effective uncertainty handling, and multi-purpose and multi-domain application. Therefore, the approach presented in this thesis attempts to solve most of the GDS challenges, and the achievement on this matter will be reported in the last chapter of this thesis.

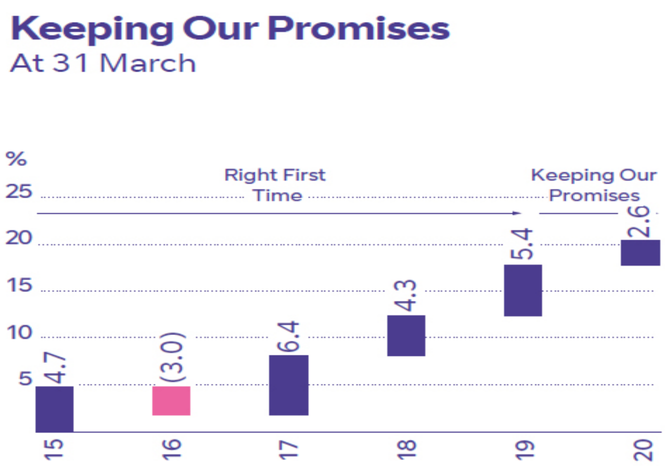

Figure 5.2. Example of a customer experience measure (Image courtesy | BT [147])

Indeed, as reported in Section 5.3, simulation in the field services operations domain has also observed various advances. However, relevant shortcomings remain present in the solutions mentioned above. These shortcomings include linear modelling and the lack of studying the effect of uncertainty, which is naturally inherent in real-world problems.

Finally, it is noteworthy to mention that in combination with the previous chapters, the aforementioned GDS approaches do not offer a suitable explanation nor interpretation of their models. Hence, the importance of a solution that provides a complete framework fully interconnected, efficient knowledge management, accountable learning capabilities, and effective uncertainty handling, which are the focus of this thesis.

The next chapter will introduce the concept of data-driven decision making, and it will present the main categories of data-driven decision making available in the literature. Moreover, it will define a data-driven model to serve as the foundation for the GDS approach being built in this thesis, introducing a strategy to leverage conventional simulation to support GDS efforts. Finally, it will introduce the metrics to evaluate a simulation scenario.

Chapter 6 - Data-Driven Decision Making

Organisations must be able to make efficient decisions, especially when these decisions dictate their competitivity in today's highly volatile business environments. In practice, there are two major approaches for decision making, namely model-driven decision making and data-driven decision making. The former refers to finding an optimal solution to an analytical programming decision model [148]. The latter refers to collecting data based on measurable key performance indicators (KPIs), discovering patterns and facts, and developing strategies towards crucial business goals [148].

Data-driven decision making (D^3M) suits better the intrinsic complexity of real-world decision problems in comparison with its model-driven decision making counterpart [148]. Particularly when the fidelity of the model results in infeasible solutions, which is commonly observed in many intelligent tools that aim to deliver an optimal solution, referred to as the "best" option [149]. However, planers and decision-makers commonly find these optimal solutions a mismatch, where reality does not meet the "best" expected outcomes.

The performance in companies that employ decision-making based on data has been studied. For example, based on a sample of about 50,000 establishments in the US manufacturing sector [150], Brynjolfsson and McElheran found evidence that management practices based on data are correlated with better performance. They concluded that, on average data-intensive decision making is associated with a statistically significant increase of 3%. A similar study was carried out based on 179 large publicly traded firms [151], in which, Brynjolfsson et al. found that productivity is higher between 5–6 % in firms that emphasize decision making based on data in comparison with other approaches. Therefore, effective data management techniques are of central importance to organisations.

Fundamentally, D^{3}M facilitates working towards business targets by ensuring data consistency, quality and representativity of the problem being solved. However, conducting D^{3}M is not a trivial task. Especially in highly regulated industries. In the UK, the Data Protection Act 2018[5] governs the processing of information relating to individuals, including how organisations, business or the government use personal information. Therefore, any data-driven solution must be compliant with data protection regulations.

This chapter introduces the concept of D^{3}M and points out the main differences with its model-driven decision making counterpart. Successively, it presents the main categories of D^{3}M available in the literature. Additionally, this chapter defines a data-drivel model as the foundation for the GDS approach being built in this thesis. It presents a strategy to leverage

5 https://www.legislation.gov.uk/ukpga/2018/12/introduction/enacted

conventional simulation to support GDS efforts. Finally, this chapter introduces the metrics that describe a simulation scenario.

6.1 Categories of data-driven decision making

This section presents the main categories available in the literature for data-driven decision making (D^3M). D^3M facilitates problem-solving towards business targets by collecting data based on measurable KPIs and pattern discovery [148]. In contrast to its model-driven decision making counterpart, D^3M is more suitable for real-world problems due to the practical infeasibility of the solutions provided by model-driven decision making approaches.

To better understand the shortcomings of model-driven decision making, Figure 6.1 depicts a traditional flow where the problem can be defined precisely by a mathematical model. Therefore, the solution is determined by the fidelity of the model. However, real-world problems commonly cannot be modelled accurately by mathematical models; this is because, very often, these models are not available [149].

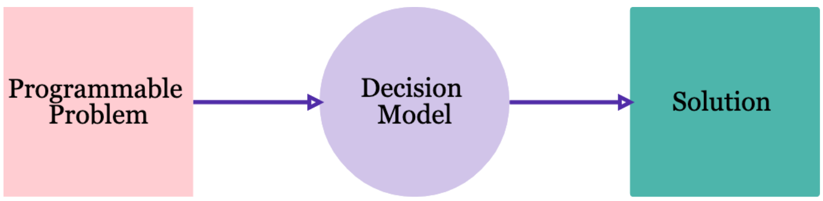

Figure 6.1. Traditional decision-making (Source: [148])

To address these shortcomings, D^3M facilitates the mechanisms to ensuring data consistency, quality and representativity. According to Lu et al. [148], the available D^3M methods can be classified into a twofold category. The first category refers to *programmable data-driven decision making* (P-D^{3}M). The second category encompasses non-programmable data-driven decision making (NP-D^{3}M).

P-D^{3}M works with the assumption that although the problem is complex, there is a programmable form for it. Examples of these type of problems can be found in multi-objective decision and multi-level decision models [152]. Here, the objective functions and fitness functions are available; thus, they are programmable. Consequently, P-D^{3}M derivates a decision model based on data mining or other data statistical techniques by implementing solutions algorithms to find an optimal solution [153].

NP-D^{3}M applies when the problem does not have a programmable form, which is the case for most real-world problems where the uncertainties and complexities of the decision process may lead to severe model mismatch [154]. For these situations, NP-D^{3}M implements a learning mechanism that discovers patterns from data and enables a rule base approach for knowledge representation extracted from data [148].

For the work presented in this thesis, there is not available objective functions nor fitness functions that model the GDS problem in the field service operations domain as previously described in previous chapters (see Chapter 2 and Chapter 5). Moreover, the approach developed in this thesis employs fuzzy logic as a mechanism for human-like problem solving (see Chapter 3 and Chapter 4). Consequently, the NP-D^{3}M classification better describes the approach implemented in this work.

The following subsections present the data collection and pattern discovery implemented in this thesis, which will be formalised in Chapter 9 as part of the resulting framework of this work.

6.2 Data-driven model

Data-driven models are focused on the analysis of the data involved in the dynamics of a specific system [155]. Data-driven models facilitate finding correlations between the inputs and outputs without exhaustive knowledge of the underlying system's behaviour. Furthermore, data-driven models enable the discovery of unforeseen patterns on raw data from real observations [155]. Moreover, real-world problems include various factors that reflect operation in the field. In other words, these could consist of additional elements initially considered by theoretical approaches. Therefore, understanding the factors involved in any problem is relevant before attempting to find its solution. Consequently, data-driven models need to implement consciously three main processes for the materialisation of effective models: data acquisition, data exploration and patterns discovery.

6.2.1 Data acquisition

Regardless of the area of study, data acquisition is a process that facilitates to conduct research by enabling to answer stated research questions, test hypotheses, and evaluate outcomes. Therefore, data acquisition focuses on systematic efforts to gather and quantify the relevant variables involved in a phenomenon of study. Data collection techniques and methods vary according to each discipline. However, there is strong emphasis across all disciplines to ensure the most accurate and honest approach [156].

In the context of this thesis, the area of study encompasses the field service operations domain, focusing on service delivery within a TSP with a presence in the UK. It can be anticipated that the work tasks and the customer premises data are essential for conducting this research. However, accessing this type of data is commonly restricted in real-world applications ranging from social sciences, humanities, business, among others. In the UK, the Data Protection Act[6]. is the regulation that controls how organisations, business and the government use personal information. Moreover, the telecommunications sector is highly regulated. Consequently, there are internal procedures to clear out in compliance with the Office of Communications, commonly known as Ofcom[7]. Appendix A presents an extract of the process for data access and sharing at BT.

The data used and analysed in this thesis was obtained in compliance with the mentioned rules, as it is the result of synthetic data generation. The use of synthetic data is a mechanism to overcome data availability issues such as data privacy, collection time, cost and diversity. Synthetic data often supports research in a range of cases, such as image data generation [157], in finance [158], and smart analytics [159], among others. *Synthetic data generation* aims to produce an accurate data set and representative of the phenomenon to be observed [160].

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[6] http://www.legislation.gov.uk/ukpga/2018/12/contents/enacted
[7] https://www.ofcom.org.uk/

After clearing out the compliance markers, synthetic data generation was conducted. As illustrated in Figure 6.2, there are different restrictions to overcome in order to generate the required data. These include virtual private network access (VPN) to be authorised to navigate from the red side into the green side. Subsequently, raw data resides in Oracle technology. Since this environment is not permitted to perform intensive computation, the relevant data needs to be migrated to the research infrastructure. Next, a data mirror needs to be created for effectively working in a dedicated environment while protecting the original retrieved raw data.

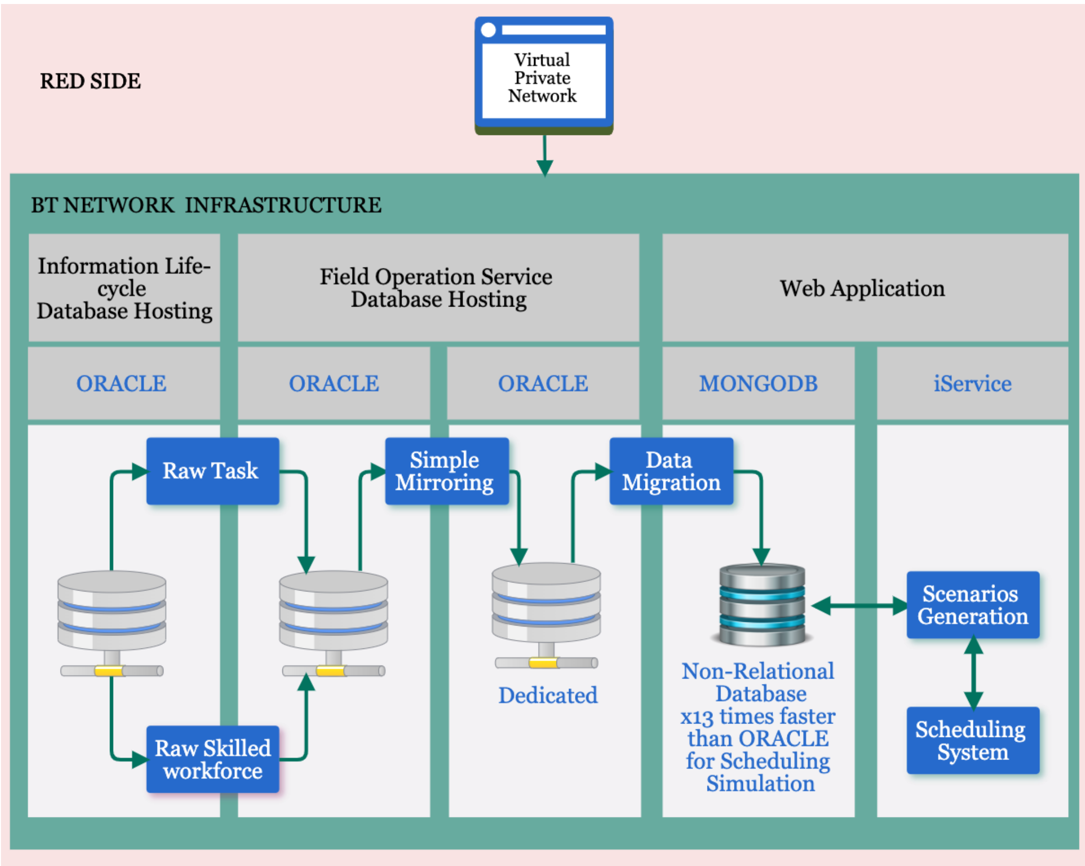

Figure 6.2. Overview of relational data access stages and its migration to non-relational

The results from the synthetic data generation process require to be migrated to a non-relational technology, MongoDB in this case. This because the obtained execution time was observed to reduce 13 times, which is beneficial for large scenarios generation. Finally, the collected synthetic data is employed to feed the scheduling system. The aforementioned process flow can be summarised as follows.

First, the skilled workforce raw data and the work tasks raw data were analysed to understand their distribution and attributes, including maximum, minimum, averages, standard deviations and variances. Next, initial data generation is performed to obtain a series of simulation scenarios as a baseline for future goal-driven computation. To achieve this, a particular domain is selected within the UK territory according to the hierarchy briefly described in Section 2.1.3. The minimum required data includes detailed information about the availability of skilled engineers and the expected tasks to be completed. Table 6.1 describes the steps for creating a set of available resources for a given scenario. Similarly, Table 6.2 presents an overall overview of the steps involved in the data manipulation for generating a single resource.

Table 6.1– Pseudocode to create a set of available resources.

Pseudocode:	Create a set of available resources
1:	Determine a random number of desired resources
1.1:	VAR_ENGINEERS := ROUND(IN_MIN_ENGINEERS + (IN_MAX_ENGINEERS-IN_MIN_ENGINEERS) * DBMS_RANDOM.value,0);
2:	Log information about the number of resources
2.1:	UPDATE GDS_SCENARIOS a SET engineers = VAR_ENGINEERS WHERE scenario_id = IN_SCENARIO_ID;
3:	Create individual resources according to the number generated in step 1
3.1:	FOR i IN 1 .. VAR_ENGINEERS LOOP GDS_CREATE_ENGINEER(IN_DATA_DATE,IN_SCENARIO_ID,IN_PROB_ABSENCE,i); END LOOP;

Table 6.2– Pseudocode to create the skilled staff.

<table>
<tr><th>Pseudocode:</th><th></th><th>Create an individual resource</th></tr>
<tr><td>1:</td><td></td><td>Personal data anonymization</td></tr>
<tr><td></td><td>1.1:</td><td>VAR_EIN := ADD_LEADING_ZEROS(IN_ENGINEER_NUMBER,9);</td></tr>
<tr><td></td><td>1.2:</td><td>VAR_PIN := ADD_LEADING_ZEROS(IN_ENGINEER_NUMBER,5);</td></tr>
<tr><td></td><td>1.3:</td><td>VAR_NAME := 'X_' || ADD_LEADING_ZEROS(IN_ENGINEER_NUMBER,5);</td></tr>
<tr><td>2:</td><td></td><td>Randomly select resource location and preferred working area</td></tr>
<tr><td></td><td>2.1:</td><td>VAR_RANDOM := DBMS_RANDOM.value;</td></tr>
<tr><td></td><td>2.2:</td><td>LS SELECT pwa, postcode INTO VAR_PWA, VAR_POSTCODE
FROM GDS_CNFG_PWA_EXCH_POSTCODE
WHERE min_val <= VAR_RANDOM AND VAR_RANDOM < max_val;</td></tr>
<tr><td>3:</td><td></td><td>Randomly select resource work types</td></tr>
<tr><td></td><td>3.1:</td><td>VAR_RANDOM := DBMS_RANDOM.value;</td></tr>
<tr><td></td><td>3.2:</td><td>ARRAY_WORKTYPES := [broadband,cal,cidt,fttc_rep, ltok, ug, copper_prov,
fttc_cease, fttc_mi, fttc_si, fttp_prov, pd_prov, tv];</td></tr>
<tr><td></td><td>3.3:</td><td>SELECT ARRAY_WORKTYPES INTO VAR_ARRAY_WORKTYPES
FROM GDS_CNFG_ENGINEER_SKILLS
WHERE min_val <= VAR_RANDOM AND VAR_RANDOM < max_val;</td></tr>
<tr><td>4:</td><td></td><td>Randomly select resource availability</td></tr>
<tr><td></td><td>4.1:</td><td>VAR_RANDOM := DBMS_RANDOM.value;</td></tr>
<tr><td></td><td>4.2:</td><td>ARRAY_ATTENDANCE := [i_rostered_mins,i_leave_mins,i_other_mins,
i_sick_mins,i_vol_ot_mins,i_auth_ot_mins,d_rostered_start,
d_rostered_end,d_lunch_start,i_lunch_duration]</td></tr>
<tr><td></td><td>4.3:</td><td>SELECT ARRAY_ATTENDANCE INTO VAR_ARRAY_ATTENDANCE
FROM GDS_CNFG_ENGINEER_ATTEND
WHERE min_val <= VAR_RANDOM
AND VAR_RANDOM < max_val;</td></tr>
<tr><td>5:</td><td></td><td>Create an entry in the resource master table</td></tr>
<tr><td></td><td></td><td>INSERT INTO GDS_OP_EMPLOYEES VALUES (IN_SCENARIO_ID,
IN_DATA_DATE, VAR_EIN, VAR_PIN, VAR_NAME);</td></tr>
<tr><td>6:</td><td></td><td>Create an entry in the resource preferred working area table</td></tr>
<tr><td></td><td></td><td>INSERT INTO GDS_TB_TECH_PWA VALUES (IN_SCENARIO_ID,IN_DATA_DATE,
VAR_EIN,VAR_PWA,VAR_POSTCODE,VAR_POSTCODE);</td></tr>
<tr><td>7:</td><td></td><td>Create an entry in the resource area table</td></tr>
<tr><td></td><td></td><td>INSERT INTO GDS_RESOURCE_AREA VALUES (IN_SCENARIO_ID,IN_DATA_DATE,
VAR_EIN,VAR_PWA,VAR_POSTCODE,VAR_POSTCODE);</td></tr>
<tr><td>8:</td><td></td><td>Create entries in the resource skills table</td></tr>
<tr><td></td><td>8.1:</td><td>IF (VAR_BROADBAND = 'Y') THEN INSERT INTO GDS_TB_TECH_SKILL
VALUES (IN_SCENARIO_ID,IN_DATA_DATE,VAR_EIN, 'BBADVREP2');
END IF;</td></tr>
<tr><td></td><td>8:N</td><td>IF (VAR_CAL = 'Y') THEN INSERT INTO GDS_TB_TECH_SKILL
VALUES (IN_SCENARIO_ID, IN_DATA_DATE, VAR_EIN,'SRCAL');
END IF;</td></tr>
<tr><td>9:</td><td></td><td>Create an entry in the resource availability table</td></tr>
<tr><td></td><td>9.1:</td><td>INSERT INTO GDS_OP_ATTENDANCE_STATE
VALUES
(IN_SCENARIO_ID,IN_DATA_DATE,VAR_EIN,IN_DATA_DATE,IN_DATA_DATE,
VAR_I_ROSTERED_MINS, VAR_I_LEAVE_MINS,VAR_I_OTHER_MINS,
VAR_I_SICK_MINS, VAR_I_VOL_OT_MINS, VAR_I_AUTH_OT_MINS,
VAR_D_ROSTERED_START,VAR_D_ROSTERED_END,VAR_D_ROSTERED_START,
VAR_D_ROSTERED_END,VAR_D_LUNCH_START,VAR_I_LUNCH_DURATION,
VAR_POSTCODE,VAR_POSTCODE,VAR_PWA);</td></tr>
</table>

Additionally, the pseudo algorithms to generate a single work task and a set of work tasks are described in Table 6.3 and Table 6.4, respectively. Posteriorly, Figure 6.3 shows an example of work tasks distribution for the selected domain. Where the actual name of the preferred working areas has been removed per supervisory recommendation due to data privacy regulation, however, it can be understood that they correspond to the names of geographical locations. As can be observed, each scenario has a defined geographical area.

Finally, the relationship between supply and demand denotes an initial scenario. As a result, this data generation process delivered a portfolio of 40,795 tasks, where 56% (22,772) corresponded to repair work and 44% (18,023) to provision work. The total estimated duration for this sample is 323,023 hours.

Table 6.3– Pseudocode to create a work task.

Pseudocode:	**Create a work task**
1:	Randomly select task location
2:	Randomly select skill and task category
3:	Randomly select importance and duration
4:	Create an entry in master task and task skills tables

Table 6.4– Pseudocode to create a set of available resources.

Pseudocode:	**Create a set of work tasks**
1:	Determine a random number of desired tasks
2:	Log information about the number of tasks
3:	Create individual tasks according to the number generated in step 1

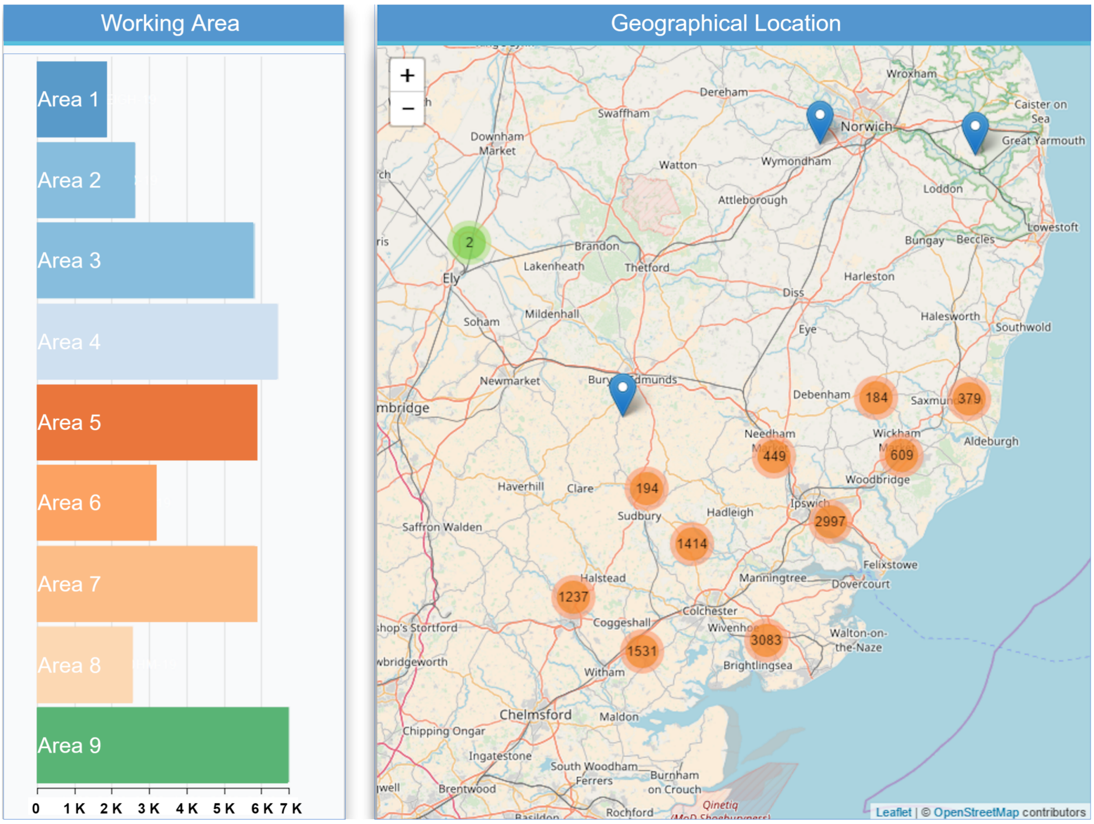

Figure 6.3. Example of task distribution by working area (left) and geographical location (right)

6.2.2 Data exploration

Exploratory Data Analysis (EDA) provides data exploration by employing visualisation techniques [161]. As part of the work presented in this thesis, a visualisation tool was developed to understand the dynamics of the field service operations. As a result, the tool enables dynamic data exploration and communication between researchers and expert users to validate assumptions among the involved stakeholders. This section provides relevant examples of the exploratory data analysis exercise.

The exploration tool was developed in a monolithic architecture, with Angular JS[8] as a front-end framework, using leaflet for interaction with maps[9], data-driven documents (D3) for manipulating documents based on data[10], MongoDB[11] as non-relational database and Java for back-end encapsulation.

Its capabilities include performing analysis by geographical location within a specific time window, locating and identifying exchanges, cabinets, task, engineers, parking events, ellipses, routes and heat maps, computing ellipse measurements, incorporating multiple resources, comparing between actual and forecasted values and spotting conflicting points.

Figure 6.4 depicts conflicting points. A conflicting point can be described as a location that is visited multiple times by an engineer. It was found that this occurs when the engineer does not have enough information or equipment to carry out the tasks on the visited premise. Conflicting points affect the business operation directly because they reduce the promise of having things done for the first time.

Successively, Figure 6.5 shows an example of actual speed versus forecasted speed. It was found that the actual speed commonly exceeds the predicted values. This phenomenon was observed when engineers need to drive in motorways in order to arrive at the customer premises.

[8] https://github.com/angular/angular
[9] https://github.com/Leaflet/Leaflet
[10] https://github.com/d3/d3
[11] https://www.mongodb.com/

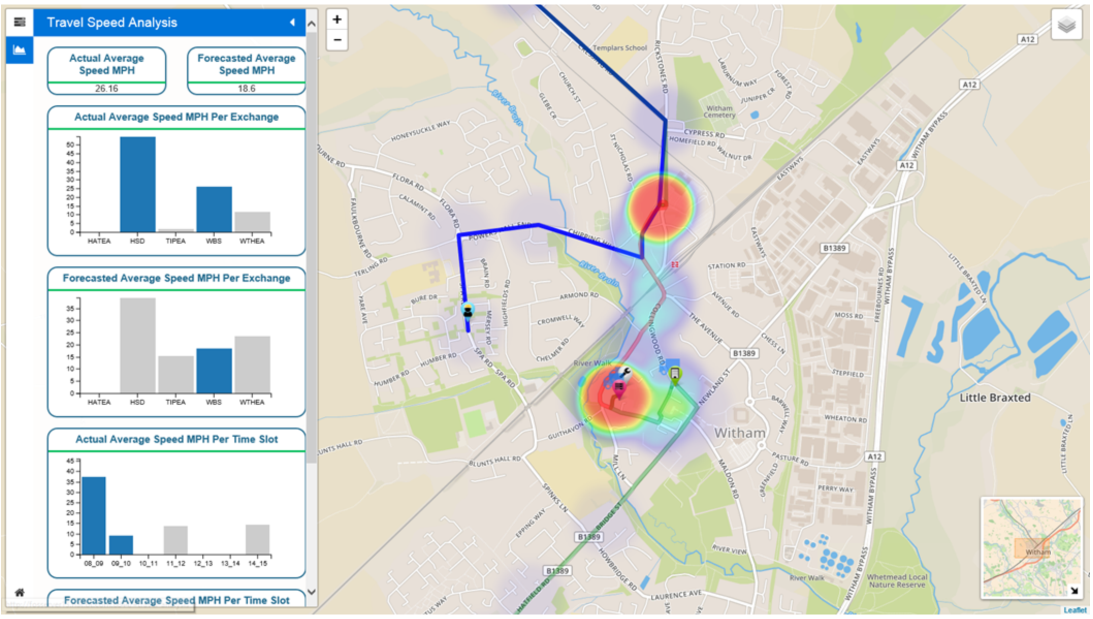

Figure 6.4. Spotting conflicting points that affect the business operation directly

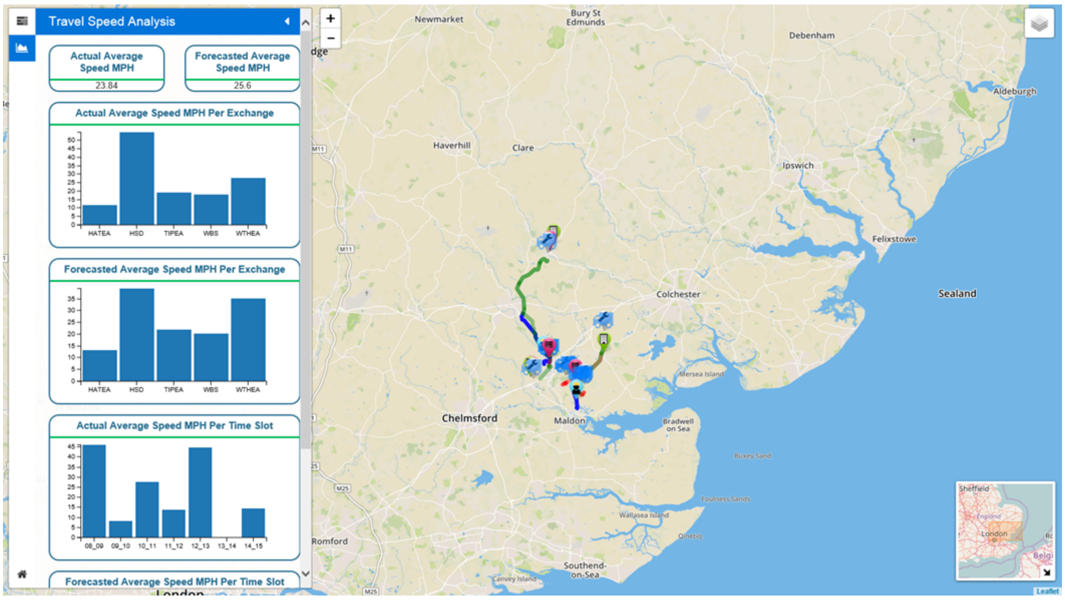

Figure 6.5. Actual speed versus forecasted speed

Figure 6.6 depicts the task travel dynamics of specific engineers. It was found more activity between 8 and 15 hrs given a working day. Similarly, Figure 6.7 shows an example of an ellipse. Ellipses facilitate measuring reasonable travel distances among an exchange, a task and a resource (i.e. engineer).

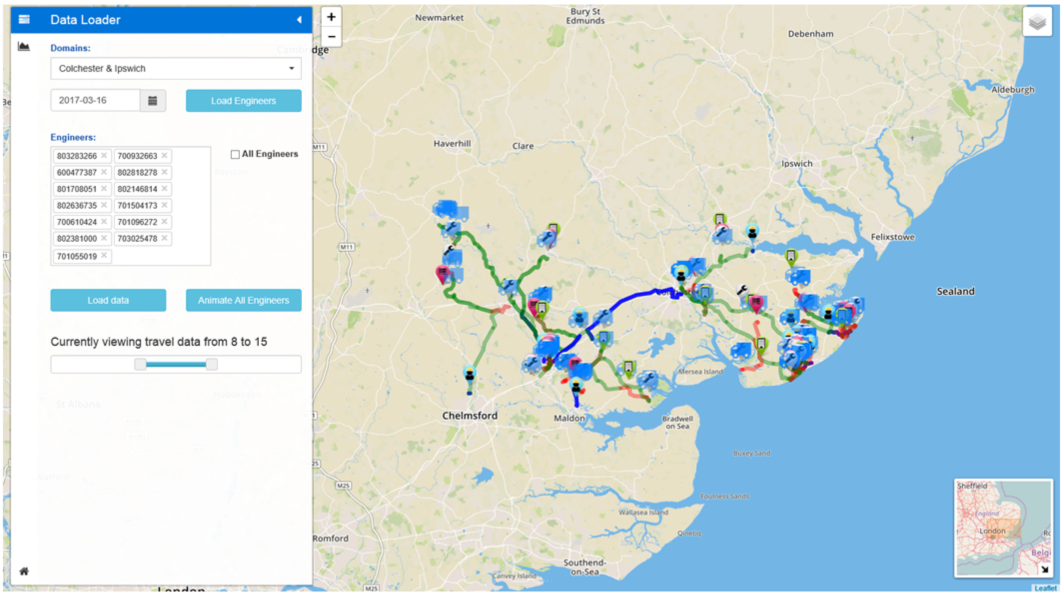

Figure 6.6. Multiple engineers, travel dynamics

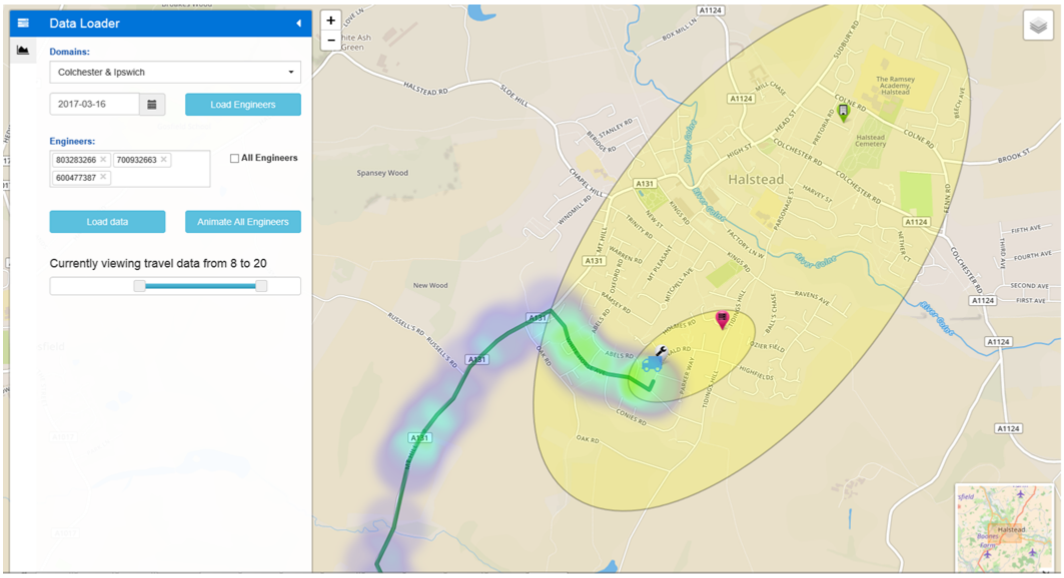

Figure 6.7. An ellipse measurement including exchange, task and resource

Figure 6.8 presents an example of an overlapping route. Overlapping routes occur when multiple engineers carry out work in premises with certain proximity. These represent an opportunity for re-assigning tasks and avoiding overlapping.

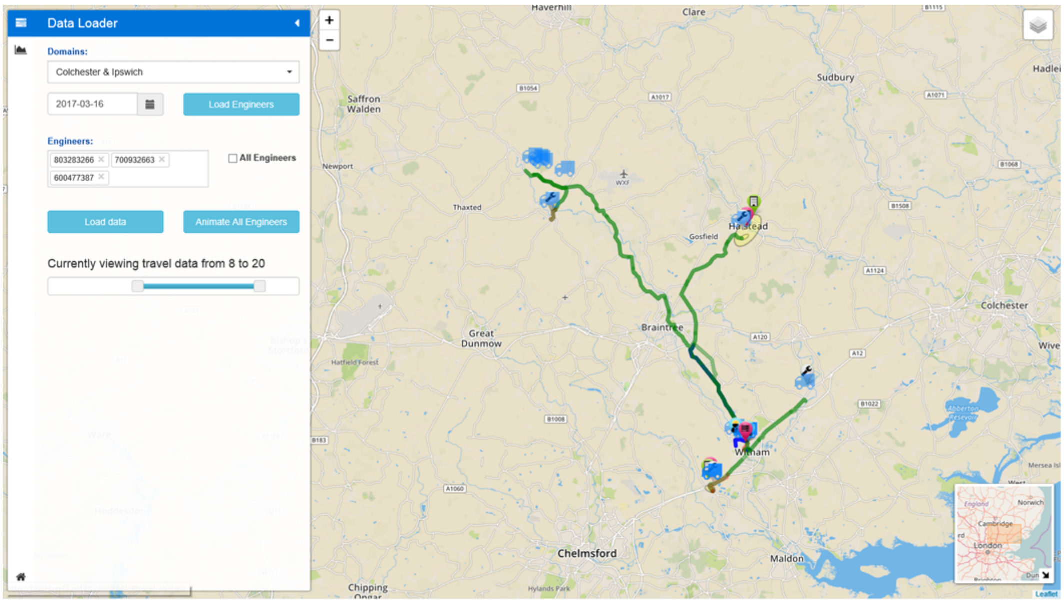

Figure 6.8. Spotting overlapping routes for a reduced number of engineers

Finally, Figure 6.9 shows exchanges, cabinets, task, engineers, parking events, ellipses, routes and heat maps. All of these employed in this analysis.

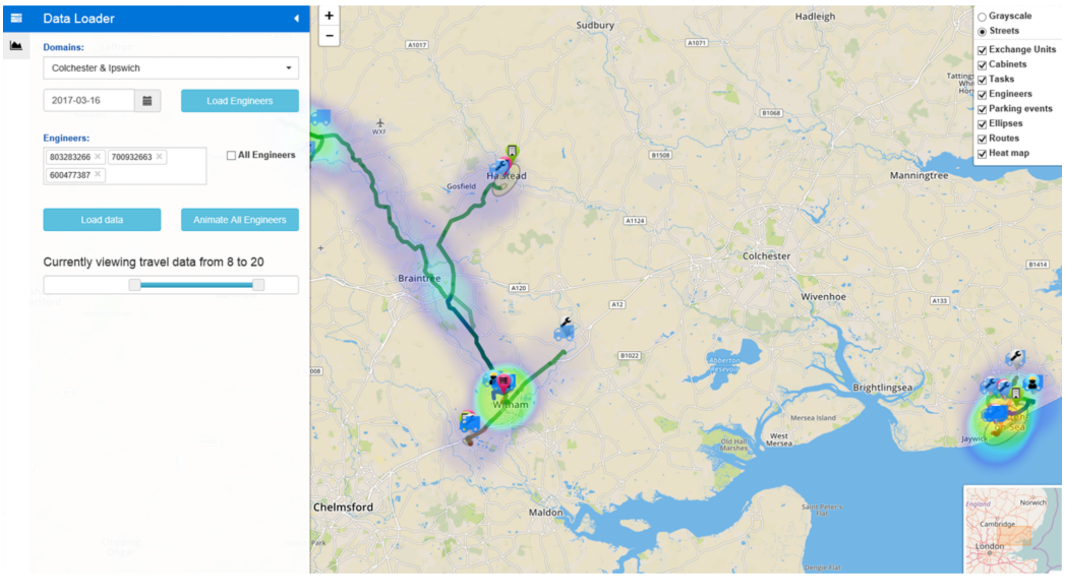

Figure 6.9. Spotting exchanges, cabinets, task, engineers, parking events, ellipses, routes and heat maps

After this analysis, the following variables were identified and incorporated into the simulation model.

- *Available tasks*: Represent the total of jobs to be completed for a specific day.
- *Original-scheduled tasks*: Indicate the total of jobs scheduled employing the currently available workforce for a determinate day.
- *Scheduled tasks*: Represent the total of jobs allocated after increasing the number of engineers in those cases when the number of engineers was not enough to assign all first jobs.
- *Available engineers*: Indicate the total of the personnel available in a specific day for job allocation.
- *Actual engineers needed*: Denote an estimation of how many extra engineers could be required to allocate the totality of jobs. This estimation is generated by the Field Scheduling System only in those cases where the initial value of engineers was insufficient to map all the task.

6.2.3 Pattern discovery

In the context of field service operation, understanding the type of data and the relevant variables embedded in the phenomenon of study is just a small part of the process. Moreover, when building simulation models, there is a strong need to identify any pattern before implementing any modelling approach. *Patterns* can be defined as a set of items or substructures that frequently occur in a data set [162]. Consequently, patterns represent the intrinsic and essential properties of datasets. *Pattern discovery* is the process of uncovering trends from large amounts of data.

In the scope of GDS, pattern discovery is vital to find and anticipate inherent regularities in the data. For field service operations, this data reflects the environment and the provision of the corresponding service to customers. Therefore, pattern discovery is the foundation of various data mining approaches [162]. These techniques vary depending on the data size, the available infrastructure and the adequate training in the modelling simulation team.

Regardless of the different techniques and possibilities for finding patterns, in this thesis, pattern discovery was conducted at the source; this is at the database level. Posteriorly, visual analytics was employed to leverage interactive geo-visualisations of activity-travel patterns. Figure 6.10 illustrates the working flow implemented to conduct pattern discovery. Each step can be summarised as follows:

- *Step 1* — raw data was obtained from the production-oriented database. As can be observed, relational databases managed by Oracle technology were the standard.
- *Step 2* — since travelling metrics are highly relevant for the field service delivery problem, a dedicated forecast model was implemented. Consequently, travel metrics such as travel time, travel distance and routes geometries were obtained from consuming services available in

the open-source routing machine (OSRM)[12] project. The OSRM project is open source; therefore, an OSRM instance was installed internally on BT servers.

- *Step 3* — a relevant metric related to carbon emissions was considered.
- *Step 4* — data aggregation techniques were applied to reduce dataset sizes.
- *Step 5* — non-relational technology was employed for performance purposes to accelerate rendering time and empower pattern finding.
- *Step 6* — data extraction logic in the back-end layer was implemented with Java technology.
- *Step 7* — data consumption was supported by document-oriented querying via JavaScript.
- *Step 8* — interactive visual analytics facilitated the exploration and confirmation of patterns.

The described data mining model enables communication with expert users to confirm whether the system is behaving close enough to real-world conditions or to clarify questions that commonly arise with the research practise. In the context of field service operations, the benefits of patterns discovery can be summarised as:

- It allows answering questions related to the dynamics or behaviour of the identified variables.

[12] http://project-osrm.org/

- It facilitates spotting if any variable is corrupted or missing from the model.
- It simplifies large data sets to practical visual summaries.
- It helps to identify distributions for each variable.
- It streamlines communication, setting common grounds.

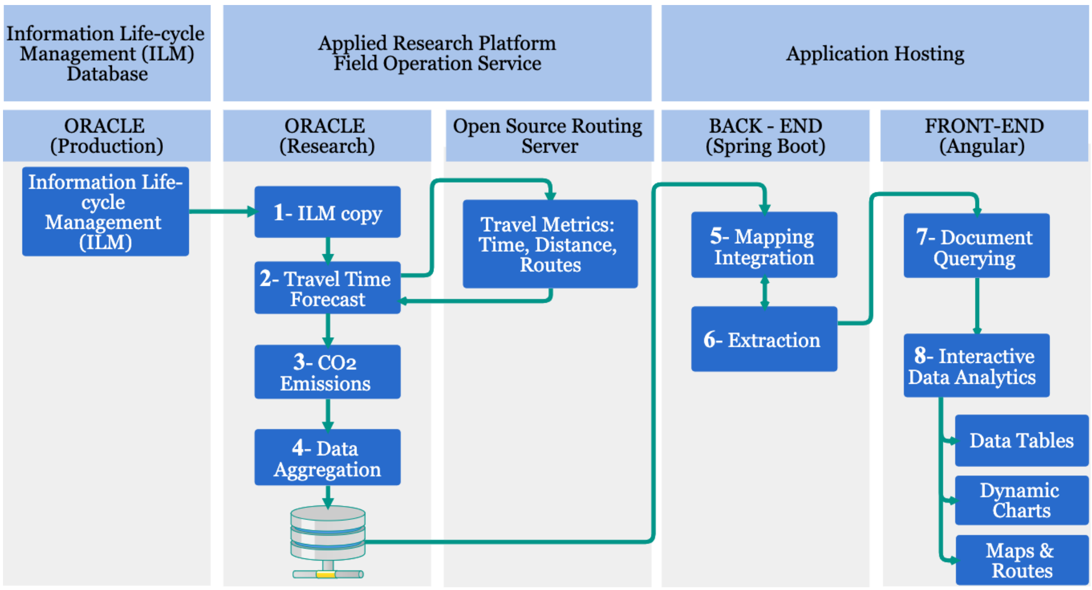

Figure 6.10. Working flow for pattern discovery

Generally, sensible data mining approaches for pattern discovery require intensive feature modelling and efficient methods for data request and data aggregation. In this regard, Table 6.5 provides an example of an entity model for an engineer, which shows its relevant attributes such as the geographical domain (for a detailed geolocation review see, Section 2.1.3), the list of travels and the list of parking events. These attributes are relevant to follow the working day of an engineer.

Table 6.5– Entity model for an engineer.

Entity Model for an Engineer

```
@Entity
@Table(name = "WM_RESOURCE")
@Cache(usage = CacheConcurrencyStrategy.READ_ONLY)
public class Engineer implements Serializable {

    @Id
    @Column(name = "EIN")
    private String ein;

    @Column(name = "PIN")
    private String pin;

    @Column(name = "DOMAIN_DESC")
    private String domainDescription;

    @Column(name = "START_LOCATION")
    private String startLocation;

    @Column(name = "START_LATITUDE")
    private Double startLatitude;

    @Column(name = "START_LONGITUDE")
    private Double startLongitude;

    private List<Travel> travels;
    private List<Travel> parkingEvents;
    private double totalTravelTime;
    private double totalTravelDistance;
```

Table 6.6 reports the travel dynamics summarisation using Oracle PL/SQL language. The aggregation plays a vital role in an active pattern analysis exercise. It will allow to trace a time-by-time activity level per engineer and combine various filters, adding or removing granularity to the analysis. Consequently, the resulting view enables low-level and high-level analytics.

Table 6.6– Example of travel dynamics summarisation.

Travel dynamics aggregation

```
SELECT
    A.ILM_DATE AS ILM_DATE,
    TO_DATE(CONCAT('01-',TO_CHAR(A.ILM_DATE,'MM-YYYY')),'DD-MM-YYYY')
AS ILM_MONTH,
    A.PAH,
    A.EIN,
    NVL(REPLACE(A.VEHICLE_MODEL, 'NULL'), 'NOT AVAILABLE') AS
VEHICLE_MODEL,
    A.GM_NAME,
    A.CST_NAME,
    TO_CHAR(A.ILM_DATE, 'DAY') AS DAY_OF_WEEK,
    TO_CHAR(A.ILM_DATE_TIME, 'HH24') AS HOUR_SLOT,
    B.GEO_TYPE_DESC AS EXCH_GEO_TYPE,
    NVL(SUM(A.DURATION_MIN),0) AS SUM_DURATION_MIN,
    NVL(SUM(A.ACTUAL_DISTANCE_MILES),0) AS SUM_DISTANCE_MILES,
    NVL(SUM(A.CO2_EMISSIONS_G_CALCULATED),0) AS SUM_CO2_G
  FROM
    ITRAVEL_FOS_DATA A ,
    ITRAVEL_MUKLCMPWA_GEOTYPES B
  WHERE  A.GROUP_CODE = B.GROUP_CODE (+)
      AND A.ZONE = B.ZONE (+)
      AND ACTIVITY_TYPE = 'MOVE'
      AND TO_NUMBER(TO_CHAR(A.ILM_DATE_TIME, 'HH24')) BETWEEN 6 AND
20
  GROUP BY
    A.ILM_DATE,
    TO_DATE(CONCAT('01-',TO_CHAR(A.ILM_DATE,'MM-YYYY')),'DD-MM-YYYY'),
    A.PAH,
    A.EIN,
    NVL(REPLACE(A.VEHICLE_MODEL, 'NULL'), 'NOT AVAILABLE'),
    A.GM_NAME,
    A.CST_NAME,
    TO_CHAR(A.ILM_DATE, 'DAY'),
    TO_CHAR(A.ILM_DATE_TIME, 'HH24'),
    B.GEO_TYPE_DESC;
```

Some non-exhaustive examples of patterns in the field service operations domain can be listed as follows. Which day is the higher carbon footprint generation? What areas represent more volume of emissions? Is the emission lower from workers that park their vehicle at home? Figure 6.11 depicts these examples.

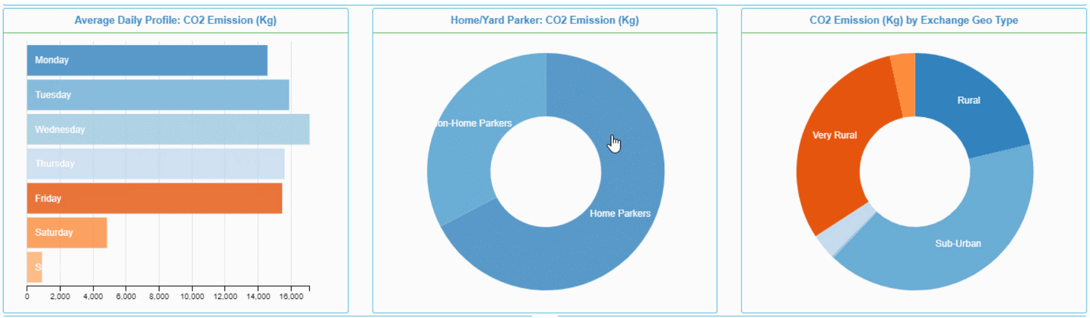

Figure 6.11. Example of patterns discovery by day, type of parker and exchange geo type

Another form of patterns relates to the behavioural description given by the time window, in which a variable is analysed by a particular unit of time. For example, Figure 6.12 reports an hourly speed profile in miles/hour (left); similarly, the distribution by geographical domain is presented (right).

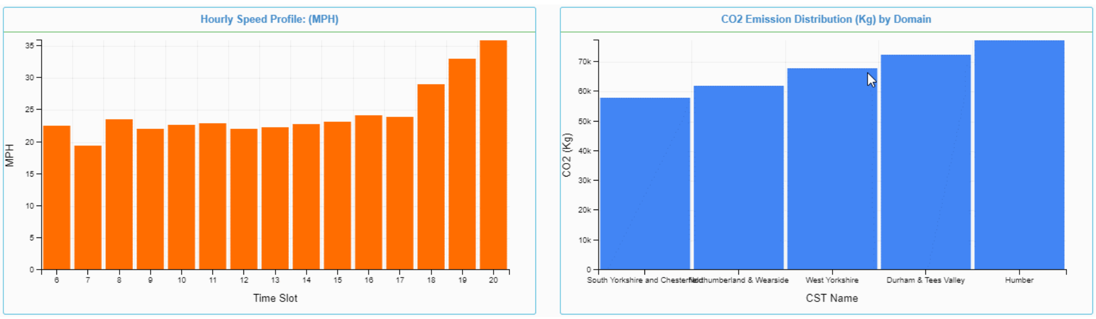

Figure 6.12. Hourly speed profile in miles/hour (left) and carbon emissions in Kg distributed by domain (right)

Another advantage of this approach is the capability of combining multiple variables visually. It is worth to remember that this approach includes interactive visual analytics. Therefore, when an element in the graph is clicked, it triggers a global filter to the whole dataset being analysed. More importantly, these filters can be added up. As a result, the discovery is multi-level and cross-functional. In this regard, Figure 6.13 depicts an hourly carbon footprint profile in Kg (left) and an hourly composite profile, including travel time in minutes and travel distance in miles (right).

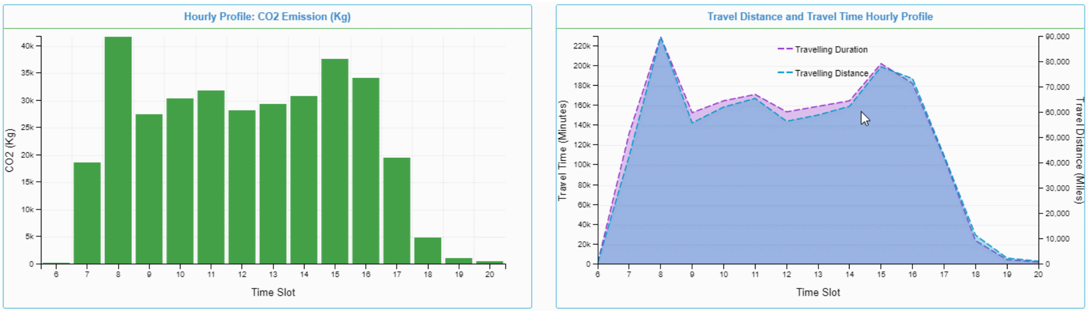

Figure 6.13. Hourly carbon footprint profile in Kg (left) and an hourly composite profile including travel time in minutes and travel distance in miles (right)

This section can conclude by pointing out that the developed pattern recognition approach allows the generation of profiles. These profiles facilitate communication with expert users to assist with the data understanding. Furthermore, it encourages discussion and team integration. Figure 6.14 shows the header for a profile with a break down in the CO_2 emissions by day.

Figure 6.14. High-level profile examples

6.3 Leverage conventional simulation to support GDS

Chapter 5 discussed the main differences between traditional and GDS approaches. One major shortcoming from conventional methods is their trial-and-error nature. In real-world applications, this is costly and affects planning productivity, diminishing the effect of decision-making.

However, the preventive capability inherent in conventional simulation enables knowing the impact of the inputs' variation for a given model. Certainty benefitting from this capability is the focus of this subsection. The following fourfold strategy has been defined to leverage conventional simulation, supporting the aim of this thesis.

First, the scheduler system employed in BT, as introduced in Section 2.1.5, is managed as a black-box. Therefore, no exhaustive internal detail is required to obtain simulation results. Second, a selection of the main inputs parameters is discussed with expert users to agree about relevant data that operational managers modify when carrying out simulation and planning tasks. Third, an automatic output generation is implemented where the inputs identified in the previous step are adjusted systematically. Fourth, the primary key performance indicators are identified, and the relationship to specific business goals is associated. The following subsections provide detailed insight into this strategy.

6.3.1 The scheduler as a black-box

As any productive system, the Intelligent Scheduling Framework 3.0 part of the FOS suite has been in constant development in BT. There is a dedicated team that maintains this tool and provides support to its users. Attempting to open and analyse its inner workings may be seen as a titanic task; mainly, because these tools are not static; they are in continuous change. Therefore, this thesis approaches it as a black-box. The interest in this tool refers to the results that it generates, and its underlying algorithms are indeed important. However, understanding their implementation and model status is not relevant to achieve the GDS capability being implemented in this work. Figure 6.15 exemplifies this black-box approach.

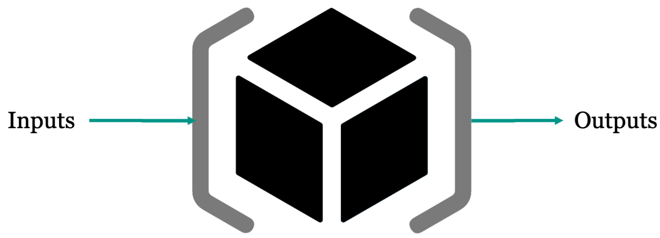

Figure 6.15. BT's scheduler system seen as a black-box

6.3.2 Main inputs in agreement with experts

Exposing the main inputs is defined in function of the influence on customer experience and in the expected demand. Consequently, in agreement with experts, the following data is identified as relevant: Geographical Domain, Quality of Service Cost, Travel Cost, Staff Profile, Demand Profile, Appointment Slots and Daily Attendance Patterns. The inputs are briefly described below.

- *Geographical Domain* refers to the granularity of the territory in which the company operates. For a detailed view on this topic, see Section 2.1.3.
- *Quality of Service (QoS) Cost* refers to the offered service and how it is evaluated. For a detailed view on this topic, see Section 2.1.2. QoS is correlated to Operational Cost.
- *Travel Cost* refers to the cost associated with travel.
- *Staff Profile* refers to the configuration of the workforce. In the service operations domain, skilled staff is commonly referred to as *resources*.
- *Demand Profile* refers to the job task to be completed. Similarly to the Staff Profile, a Demand Profile can be increased or decreased by a certain percentage. It also can focus on a specific skill or all skills and allows to select any particular area or all geographical areas. The only difference with its counterpart Staff Profile is that Demand Profile allows configuring the duration of appointments.
- *Appointment Slots* refer to the preferred time window for attending appointments, which indicates the preference to agree visit times with customers. The configuration in this regard is simple; it only needs the work type to focus on, the appointment start-time and the end-time.
- *Daily Attendance Patterns* refer to the preferred attendance of the skilled staff. Attendance patterns indicate the beginning and finishing of the working journey. Lunchtime is also reported, this to avoid work assignment on that time slot.

6.3.3 Automation of conventional simulation

Once the relevant inputs have been recognised, the variation of those inputs can be achieved by an automated process. This automation aims to modify the identified data and to feed them to the black-box simulator. Therefore, new results will be generated for each systematic variation. This approach allows the generation of new scenarios that reflect these variations. It is noteworthy to point out that at this point, these new scenarios are meaningless because they are not linked to any particular business target. However, the value of these scenarios is that they reflect the effect of the whole set of inputs. This information will be useful if the fuzzy logic learning step described in the next chapter. Figure 6.16 reports a schematic representation of the variation of the inputs to be fed into the black box.

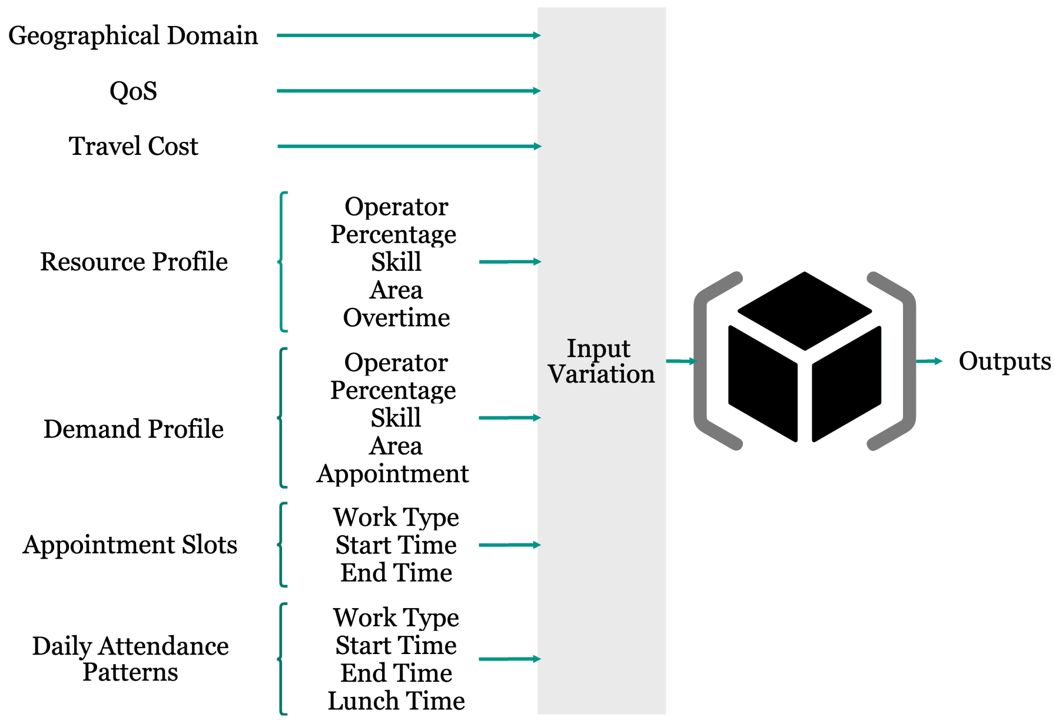

Figure 6.16. Automatic input variation for conventional simulation

6.3.4 KPIs from conventional simulation

The results per each conventional simulation can be interpreted in two ways, first; as high-level results, which indicate the main numbers of the scenario. For example, Figure 6.17 reports high-level results for three different scenarios. These results focus on selected elements, including available resources, available tasks, resources with an assigned job, scheduled tasks, travel hours spent, task hours spent, locations visited, available work hours, available working hours, and allocated working hours. These results provide a quick insight into the effects of each situation. However, these values do not reveal the productivity of such scenarios. Therefore, a more in-depth analysis is required.

Selected Scenarios

Scenario ID	Number of Available Resources	Number of Available Tasks	Number of Resources With Job	Number of Scheduled Tasks	Number of Completed Tasks	Number of Furthered Tasks	Travel Hours Spent	Task Hours Spent	Number of Locations Visited	Available Work Hours	Available ManHours	Allocated ManHours
Demo1	132	477	131	272	N/A	N/A	85.75	387.32	70	631.13	1056	1048
Demo2	118	398	116	398	N/A	N/A	117.83	526.28	77	526.28	944	928
Demo3	146	517	138	517	N/A	N/A	119.12	686.05	77	686.05	1168	1104

Figure 6.17. Example of high-level results for three scenarios

The concept of scenario metrics is introduced to address this issue. *Scenario metrics* allow evaluating the quality of the results of the simulation results. Figure 6.18 presents the metrics resulting from a given scenario. As can be observed, the column labelled as measure reports the computed metrics; for example, the Scheduled Task Percentage metrics reports 57.02% for this scenario. Each scenario has its own metrics; therefore, the metrics for each situation represent its characteristics, and these reflect the effect of the input variation introduced in the previous subsection. Figure 6.19 illustrates this by presenting measures for another scenario, with 100% of the scheduled tasks.

Measure	iService
Scheduled Tasks Percentage	57.02
N available Tasks	477
N Available Resources	132
N Provision Apmt Success	43
N Provision Apmt Failure	67
N Provision NonApt Success	7
N Provision NonApt Failure	52
N Repair Apmt Success	200
N Repair Apmt Failure	20
N Repair NonApt Success	22
N Repair NonApt Failure	66
N Missed Appointments	87

Figure 6.18. Metrics for a given scenario

Measure	iService
Scheduled Tasks Percentage	100
N available Tasks	398
N Available Resources	118
N Provision Apmt Success	94
N Provision Apmt Failure	0
N Provision NonApt Success	48
N Provision NonApt Failure	0
N Repair Apmt Success	180
N Repair Apmt Failure	0
N Repair NonApt Success	76
N Repair NonApt Failure	0
N Missed Appointments	0

Figure 6.19. Metrics for a scenario with 100% of scheduled tasks

Mostly, some performance indicators can be defined from these metrics. For example, computing the scheduling rate SR for a given scenario i can be obtained as follows:

$$SR_i = \frac{PA_i + PNA_i + RA_i + RNA_i}{J_i} \times 100\% \tag{6.1}$$

where scheduling rate SR for a given scenario i is given in function of PA_i and PNA_i, which, denote the number of successfully scheduled provision appointments and non-appointments for a given scenario i, respectively. Similarly, RA_i and RNA_i represent the number of successfully scheduled repair appointments and non-appointments for a given scenario i, respectively. Finally, J_i represents the total of the available task to be scheduled for a given scenario i. A comprehensive list of symbols employ to describe the scenario metrics is given at the start of the thesis.

6.4 Discussion

This chapter has introduced the concept of data-driven decision making and pointed out the main differences with its model-driven decision making counterpart. Successively, it presented the main categories of data-driven decision making available in the literature. Then, this chapter defined a data-drivel model to serve as the foundation for the GDS approach being built in this thesis. Subsequently, it outlined the data acquisition strategy, the data exploration techniques and the pattern recognition methodology. Successively, this chapter presented a strategy to leverage conventional simulation to support GDS efforts. Then, it detailed this strategy by indicating how to see BT's scheduler system as a black-box. Successively, it reported the agreed inputs with experts, and it showed the logic for automation of conventional simulation. Finally, this chapter presented the metrics to evaluate a scenario simulation.

Each section of this chapter has been devoted to stressing the importance of a functional data model as the core for data-driven decision making approaches. Having an operational data model is crucial given that in most of the data-based projects, a high percentage of the time assigned for the project is destinated to data-related tasks such as data collection, management, cleaning and labelling, among others. In this regard, a survey found that 51% of the time was used for data-related tasks [163]. Furthermore, the online community of data scientists and machine learning practitioners Kaggle found that gathering, cleaning and visualising data takes 11%, 15% and 9%, respectively [164], which add up to 35% of the total available time. Hence, the relevance of a complete approach to supporting data-driven decision making, as outlined in this chapter.

In summary, D^3M facilitates working towards business targets by ensuring data consistency, quality and representativity of the problem being solved. Companies that use D^3M approaches report between 3—6% of higher productivity in comparison with its model-driven decision making counterpart [150] and [151]. The main categories for D^3M are P-D^3M and NP-D^3M. P-D^3M works with complex problems that have a programmable form. Common examples of this approach are multi-objective decision and multi-level decision models [152]. In contrast, NP-D^3M applies when the problem does not have a programmable form. This approach suits better real-world scenarios where NP-D^{3}M facilitates a learning mechanism that discovers patterns from data and enables a rule base approach for knowledge representation extracted from data [148]. It is worth to point out that the GDS approach being presented in this thesis corresponds to this second category, namely, NP-D^{3}M.

A sound data-driven model must include mechanisms for data acquisition, data exploration and pattern discovery. The data acquisition approach introduced in this chapter included an end-to-end flow from raw data to scenario generation. It included a migration steep from relational to non-relational technology, which signified an improvement of 13 times, on average. Data protection was taken seriously; therefore, the data acquisition approach was designed in compliance with BT sharing rules guidelines.

Data exploration was carried out with the support of visualisation techniques, which delivered interactive visual analytics capabilities. It is worth noting that the presented visualisation tool was created from scratch as part of the work of this thesis, which is a valuable tool to identify the dynamics of the field service operations at a practical level.

A methodology for pattern discovery was presented. It included an end-to-end flow from individual engineer activity to aggregation. This methodology facilitated the creation of an interactive visual analytics tool, which was created as part of the work presented in this thesis. The developed capabilities included pattern discovery by day, type of parker, exchange geo type, hourly speed profile, carbon emissions in Kg distribution by domain, hourly carbon footprint profile in Kg, and travel time in minutes and travel distance, among others. All the mentioned patterns were summarised in a high-level profile, which can be seen as a valuable approach to facilitate communication between experts and the author of this thesis to clarify the field service operations and the relevant factors for efficient scenario operativity.

Finally, a complete methodology was presented to leverage traditional simulation approaches to support GDS. Fundamentally, this approach allows benefiting from almost 25 years of experience that BT's scheduler system has. By seeing BT's scheduler as a black-box, the speed for GDS modelling improved significantly. This, mainly because no extra time was required to understand its underlying algorithms. Instead, the focus was on the results. This approach allowed to create a satellite application focused only on the generation of scenarios via simulation exercises. In this context, a simulation occurs when the inputs are fed into the scheduler system in a controlled environment. This environment retrieves the results and manages each scenario by recording its characteristics for further knowledge discovery, which will be carried out by the fuzzy system, which will be discussed in more detail in the next chapter.

Undoubtedly, the importance of a strategy for data is fundamental to the success of data-driven applications. This chapter has strived to provide a sensible and sound approach which resulted in the development of two tools that benefit from visual analytics to facilitate modelling and, most importantly, communication with experts.

However, as illustrated during the development of these chapters, complex problems require more than interactive visual analytics and smart aggregation techniques. Hence, the relevance of the GDS approach presented in this thesis. The next chapter will introduce an incremental approach to develop a type-1 fuzzy logic system and will walk through its extension to type-2 fuzzy logic systems. Moreover, it will present the first result of applying fuzzy logic to the GDS problem.

Chapter 7 - Agile Modelling for Fuzzy Logic System Development

Due to the current technological state, in which business operations are highly automated, there is a need for better solutions to assist decision making. These solutions should excel in providing an agile and intelligent framework, which must benefit various areas of companies' business activity. Effective design and development of such intelligent solutions is not a trivial endeavour. Mainly due to complex operational conditions that are inherent in real-world economic activities. Examples of this include unexpected disturbances in the demand or difficulties in provisioning, among many others.

Moreover, uncertainty generates variations between the expected and the actual outcomes. When these variations are favourable, they can spot new opportunities. Otherwise, they can result in threats to companies' market presence and profitability. Consequently, solutions that support decision making aim to safeguard companies' business sustainability by providing optimal, agile and intelligent capabilities that are aligned to the operational conditions.

Commonly, these solutions are supported by mathematical and theoretical models in the form of computer algorithms. The effectiveness of these models depends upon their proximity to feasible and real conditions. Consequently, GDS emerged to imitate real-world processes over a specific time window. GDS is useful in assisting various problems such as forecasting, obtaining behavioural insight, and heuristic-based solutions, among others.

Fundamentally, GDS attempts to find adequate values for a set of inputs to achieve the desired output. If the adopted GDS approach is robust and reflects carefully real-world conditions, then its solutions are expected to be feasible. However, most of the current real-world situations are multivariate, along with multiple components. Besides, such solutions often include unforeseen disturbances resulting in uncertainty and non-linearity. Therefore, GDS attempts to determinate an input configuration required to accomplish the desired target by taking all these elements into account.

As a result, solutions based on GDS approaches combine various levels of complexity into their architectural models. Ultimately, any solution that supports decision making should aim to protect business sustainability. Specifically, these solutions should take into consideration elements such as companies' financial situation, regulatory compliance, and social and environmental risk. Consequently, GDS approaches are both theoretical and highly practical. Due to this importance, GDS is relevant in the applied operational research domain for companies that are capital-intensive with a strong focus on improving their service delivery. This applies to supplier companies, including Telecommunication Service Providers (TSPs) and the utility sector, including gas, and water firms, among others.

This chapter introduces an agile modelling approach to develop fuzzy logic systems. Successively, it presents the incremental phases in the construction of the proposed GDS in the scope of the workforce allocation domain by detailing the first type-1 fuzzy logic system and its extension to type-2 FLS. Results show that, on average, the type-2 FLS outperformed its counterpart type-1 FLS by 29% in training. Similarly, in the testing phase, the type-2 FLS kept its superiority with 27% over the type-1 FLS. Analogously, the main benefits achieved at this phase are demonstrated, which include: the ability to establish the portfolio configuration to achieve the desired business goals without experiencing the trial-and-error shortcomings; the FLSs suitability for handling multiple goals; the capacity to generate sensible results within a reasonable time frame; and the reveal of the underlying modelling by walking users through the incremental design.

7.1 Agile modelling for fuzzy logic systems development

Design and development of simulation models is a knowledge-intensive process, which shares various aspects of software engineering—specifically, those aspects related to development, testing, deployment and project management [165]. Moreover, creating simulation models demands flexible development approaches that facilitate a quick adaptation in case of changes arise. Changes are constant in the research practice. Hence, the need to adopt a working methodology that suits this aim.

Mostly, two main approaches support software-based project management. These are traditional methods, also known as Tayloristic and agile [166]. There are multiple flavours of agile development methods. In principle, all agile methods are based on the Agile Manifesto[13].

While most of the agile methods focus on programming aspects, Agile Modelling (AM) centres modelling, primarily on how to model effectively under the agile perspective. AM does not focus on software development methods. Instead, AM prioritises modelling with model-oriented principles such as *incremental change*, *model with a purpose*, and *local adaptation*, among others. In addition, it can be used with any software development approach [165].

As a result, the GDS approach is being developed incrementally, with specific purposes at any stage and willing to adopt changes if they are required. This first stage includes the development of type-1 and type-2 fuzzy logic systems, conducting initial experiments and establishing a benchmark for suitability of providing sensible solutions for the GDS problem in the field service delivery domain. The next subsections develop this methodology and cover the phases mentioned above.

7.2 Initial type-1 fuzzy logic system for GDS

Building a GDS for field service delivery presents some challenges, for example, sparse expert knowledge to assist during the design process. Moreover,

[13] https://agilemanifesto.org/

introducing fuzzy theory to stakeholders might not benefit from fast adoption. Notably, fuzzy theory offers flexibility and generates an agile approach for building the model progressively.

For the case of sparse expert knowledge, it is acceptable to use the approach of equally spaced triangular fuzzy sets [167]. In this regard, the benefit of using a higher number of membership functions to obtain more significant results was studied in [57]. Therefore, the initial modelling employs seven linguistic labels. These are {*very very low, very low, low, medium, high, very high, very very high*}. The following subsection will walk through each step of the construction of the type-1 membership functions.

7.2.1 Construction of type-1 membership functions

As described in Section 6.2.1, each input parameter has its own computation to determine the values corresponding to maximum, minimum, averages, standard deviations and variances. Therefore, determining the vertices of the corresponding membership function is based on these characteristics for each variable. This means that the start, top and end values of the shape are not fixed. Therefore, the implemented approach is capable of adapting and modelling the corresponding membership function according to the input/output vector being processed.

The corresponding fuzzy set A in the X universe of discourse for an x element is a set of ordered pairs: $A\{x, \mu_A(x) | \, x \in X\}$ where $\mu_A(x)$ is the corresponding membership function of x in A. Following an agile modelling, the initial implementation encompasses triangular and trapezoidal membership functions. Other shapes will be incrementally introduced in the next chapters. A triangular membership function is defined as follows [168]:

$$\mu_A(x; a, b, c) = \begin{Bmatrix} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & c \leq x \end{Bmatrix} \tag{7.1}$$

where a represents the lower limit, b denotes the support point, and c represents the upper limit of the triangular shape. Figure 7.1 illustrates a triangular shape by employing the abovementioned points a, b and c.

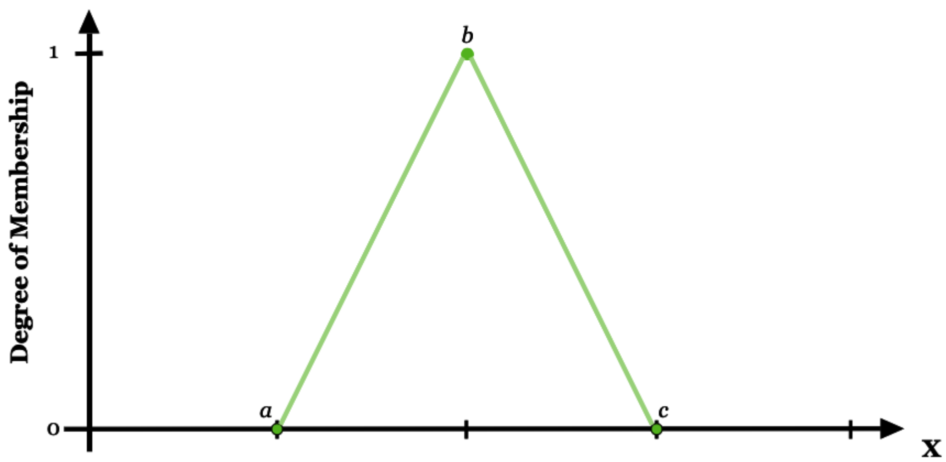

Figure 7.1. Representation of a triangular membership function (Source: [58])

In practice, the combination of triangular with trapezoidal shapes helps to represent better the minimum and maximum ranges of the universe of discourse X [168]. Consequently, in this first version of the type-1 FLS, the trapezoidal and triangular shapes are combined. Trapezoidal shapes can be defined by four points specified in the vector $[a\ b\ c\ d]$. Consequently, the set A is represented by its membership function as follows [168]:

$$A \rightarrow \mu_A(x \mid [a\ b\ c\ d]) \tag{7.2}$$

where the support points b and c define the shoulders and the lower and upper limits are defined by the points a and d, respectively. Consequently, a trapezoidal membership function is defined as follows [168]:

$$\mu_A(x; a, b, c, d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \tag{7.3}$$

Therefore, when $b \equiv c$ the resulting membership function is the triangular shape, with parameters $[a\ b\ d]$. Similarly, when $b \equiv a$ the resulting shape is a trapezoidal left shoulder. Analogously, when $c \equiv d$ the resulting membership corresponds to a trapezoidal right shoulder. Figure 7.2 depicts each one of these memberships.

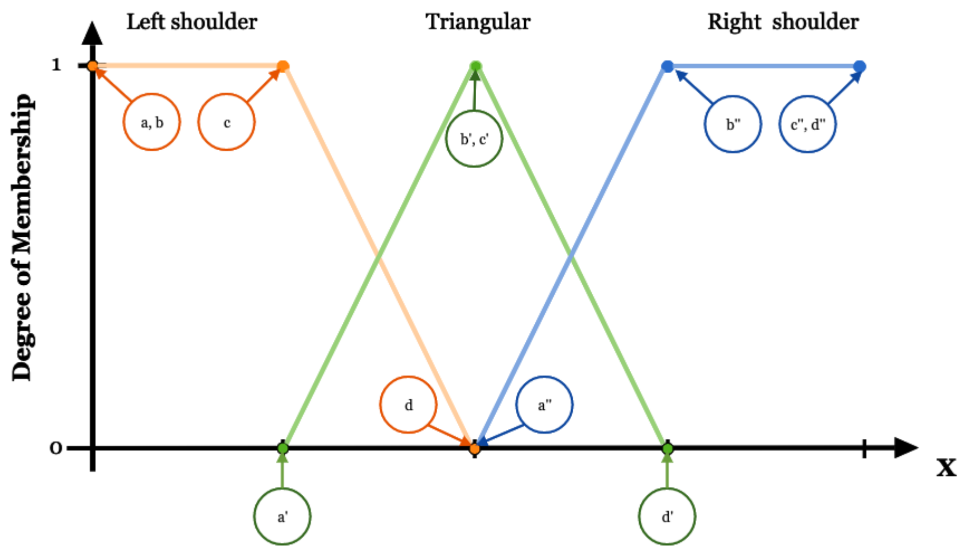

Figure 7.2. Trapezoidal and triangular membership functions (Source: [58])

This thesis proposes an automatic membership generation based on the input/output vector characteristics. Therefore, for equally spaced fuzzy sets, obtaining a trapezoidal left shoulder, triangular, or trapezoidal right shoulder fuzzy set depending on the input/vector characteristics can be achieved as follows:

$$S_t = \begin{Bmatrix} a\,, \\ \left(1 + sgn\left(-2\,t\; + \;(t\; + \;1)\right)\right)\, a + sgn(t-1)\, b, \\ sgn\,(T\; - \;t\,)\, c + \left(\,1\; - \;sgn\;(t\;mod\;T\,)\right) d\,, \\ d \end{Bmatrix} \tag{7.4}$$

where, S represents a subset of A for a t^{-th} linguistic term. A was previously formalised in Equation 7.2. A linguistic term is denoted by $t = \{1,2,..,T\}$. T represents the total number of linguistic terms. The modulo operation given two numbers t and T is expressed by $t\;mod\;T$, which can be defined as the remainder of the numerical division of t by T [169]. The direction of the shape is determined by the sgn function, which represents the sign of a real number. This can be negative, zero or positive for a real x as follows [170]:

$$sgn(x) = \begin{cases} -1 & for\; x < 0 \\ \;\;0 & for\; x = 0 \\ \;\;1 & for\; x > 0 \end{cases} \tag{7.5}$$

Therefore, the full fuzzy set A can be obtained by the collection of all points $x \in X$ with their associated membership function $\mu_A\,(x)$. Therefore, the set theoretic operation of union can be expressed as follows [171]:

$$\forall x \in X:\; \mu_{\bigcup_{t\in T}^{\cdot} S_t}(x) = \textstyle\sum_{t\in T} \mu_{S_t}\,(x) \tag{7.6}$$

where S is a subset as defined in Equation 7.4 for a t linguistic term. A linguistic term is denoted by $t = \{1,2,..,T\}$. T represents the total number of linguistic terms and $\sum$ denotes the theoretic operation of union.

As illustrated in Figure 7.2 the elements of the vector $[a\ b\ c\ d]$ can take different values. These variations will define the full fuzzy set. The following relations facilitate computing each element of the vector $[a\ b\ c\ d]$, respectively:

$$a = \frac{Mx_p(t-1)}{T} - \theta \tag{7.7}$$

$$b = \frac{Mx_p\,(2t-1)-\theta T}{2T} \tag{7.8}$$

$$c = \frac{Mx_p\,(2t-1)-\theta T}{2T} \tag{7.9}$$

$$d = \frac{Mx_p t}{T} \tag{7.10}$$

where $t = \{1,2,..,T\}$ represents the t^{-th} linguistic term, Mx is the maximum value of the parameter p, T is the total of linguistic terms and θ is an overlap grade initialised first from a random seed.

7.2.1.1 Demonstration of automatic type-1 membership functions generation

The abovementioned principles for automatic type-1 memberships generation can be demonstrated by simple value substitution in the equations mentioned above. It worth to point out that it is acceptable to use equally spaced fuzzy sets [167]. Therefore, equally spaced fuzzy sets will be implemented in this first version. Moreover, in Section 6.3, a comprehensive review of inputs, outputs and relevant metrics was disclosed. Consequently, Table 7.1 reports an example of the data characteristics that will demonstrate the type-1 automatic generation.

Table 7.1– Values to demonstrate automatic type-1 membership functions generation.

Abbreviation	Value	Description
p	Available tasks	The input parameter.
Mx	504	The maximun value for the available tasks vector.
T	7	The total number of linguistic labels. In other words, is the size of the vector: [*very very low, very low, low, medium, high, very high, very very high*].
t	$\{1,2,..,T\}$	The number of linguistic term with possible values $t = \{1,2,..,T\}$. For example, 1 corresponds to *very very low* and 7 corresponds to *very very high*.
θ	19	A seeded overlap grade.

Therefore, in the computation stated in Equation (7.4) for S_t the following elements are replaced: $t = 1$ which is equivalent to {*very very low*}, $T = 7$. Note that the substituted values have been highlighted in **bold** to facilitate their identification.

$$S_t = \left\{ \begin{matrix} a\,, \\ \Big(1 + sgn\left(-2(\mathbf{1}) + (\mathbf{1} + 1)\right)\Big)\, a + sgn(\mathbf{1} - 1)\, b, \\ sgn\,(\mathbf{7} - \mathbf{1})\, c + \Big(1 - sgn\,(\mathbf{1}\ mod\ \mathbf{7})\Big)\, d\,, \\ d \end{matrix} \right\} \tag{7.11}$$

Solving the expression indicated in Equation (7.11) can be achieved step by step as follows.

$$S_1 = \left\{ \begin{matrix} a\,, \\ \Big(1 + sgn\left(\mathbf{-2} + (\mathbf{2})\right)\Big)\, a + sgn(\mathbf{0})\, b \\ sgn\,(\mathbf{6})\, c + \Big(1 - sgn\,(\mathbf{1})\Big)\, d\,, \\ d \end{matrix} \right\} \tag{7.12}$$

$$S_1 = \begin{Bmatrix} a\,, \\ \left(1 + sgn\,(\mathbf{0})\right) a + (\mathbf{0})\, b, \\ (\mathbf{1})\, c + \left(1 - \ (+\mathbf{1})\right) d\,, \\ d \end{Bmatrix} \tag{7.13}$$

$$S_1 = \begin{Bmatrix} a\,, \\ (1 + \mathbf{0})\, a + (\mathbf{0})\, b, \\ (\mathbf{1})\, c + \ (1\ - \mathbf{1})\, d\,, \\ d \end{Bmatrix} \tag{7.14}$$

$$S_1 = \begin{Bmatrix} a\,, \\ (\mathbf{1})\, a\ +\ (\mathbf{0})\, b, \\ (\mathbf{1})\, c\ +\ (\mathbf{0})\, d\,, \\ d \end{Bmatrix} \tag{7.15}$$

$$S_1 = \{\, a, a, c, d \,\} \tag{7.16}$$

where the subset S_1 can be found with the points of the vector $[a, a, c, d]$. Now, let us simply substitute the values of a, c, d as indicated in the Equations (7.7), (7.9) and (7.10), respectively as follows:

$$S_1 = \left\{ \frac{Mx_p(t-1)}{T} - \theta, \frac{Mx_p(t-1)}{T} - \theta, \frac{Mx_p\,(2t-1) - \theta T}{2T}, \frac{Mx_p t}{T} \right\} \tag{7.17}$$

From Table 7.1 we can retrieve for the parameter p corresponding to available tasks the values for $Mx = 504$, $t = 1$, $\theta = 19$ and $T = 7$. Therefore, the corresponding substitution in Equation 7.7 is highlighted in **bold** as follows:

$$S_1 = \left\{ \frac{\mathbf{504}(\mathbf{1}-1)}{\mathbf{7}} - \mathbf{19}, \frac{\mathbf{504}(\mathbf{1}-1)}{\mathbf{7}} - \mathbf{19}, \frac{\mathbf{504}(2\cdot\mathbf{1}-1) - \mathbf{19}\cdot\mathbf{7}}{2\cdot\mathbf{7}}, \frac{\mathbf{504}\cdot\mathbf{1}}{\mathbf{7}} \right\} \tag{7.18}$$

Solving the arithmetic operations, we obtain the data points in the universe of discourse that correspond to the first subset S_1:

$$S_1 = \{-19,\ -19,\ 26.5,\ 72\} \tag{7.19}$$

This process is iterative for each value of $t = \{1, 2, \dots, T\}$. For brevity, the substitutions will be omitted and only the resulting subsets are being reported. To see a step-by-step calculation for each subset see Appendix B. The resulting subsets $S_1, S_2, \dots S_7$ are as follows:

For $t = 2$, which represents $\{very\ low\}$ we have:

$$S_2 = \{ a , b, c , d \} \tag{7.20}$$

$$S_2 = \{53,\ 98.5,\ 98.5,\ 144\} \tag{7.21}$$

Similarly, for $t = 3$, which represents $\{low\}$ we have:

$$S_3 = \{a , b, c , d \} \tag{7.22}$$

$$S_3 = \{125,\ 170.5,\ 170.5,\ 216\} \tag{7.23}$$

Correspondingly, for $t = 4$, which represents $\{medium\}$ we have:

$$S_4 = \{a , b, c , d \} \tag{7.24}$$

$$S_4 = \{197,\ 242.5,\ 242.5,\ 288\} \tag{7.25}$$

Comparably, for $t = 5$, which relates to $\{high\}$ we have:

$$S_5 = \{ a , b, c , d \} \tag{7.26}$$

$$S_5 = \{269,\ 314.5,\ 314.5,\ 360\} \tag{7.27}$$

Similarly, for $t = 6$, which represents $\{very\ high\}$ we obtain:

$$S_6 = \{a , b, c , d \} \tag{7.28}$$

$$S_6 = \{341,\ 386.5,\ 386.5,\ 432\} \tag{7.29}$$

Finally, for $t = 7$, corresponding to {*very very high*} the subset can be found at the points:

$$S_7 = \{a\ , b, d, d\ \} \tag{7.30}$$

$$S_7 = \{413,\ 458.5,\ 504,\ 504\} \tag{7.31}$$

Lastly, the fuzzy set for *available tasks* is the result of the union of every obtained subset $S_1, S_2, S_3, S_4, S_5, S_6$ and S_7, as indicated in Equation (7.6). The resulting membership functions are shown in Figure 7.3. For illustration purposes, each subset has been labelled with its corresponding S_t value.

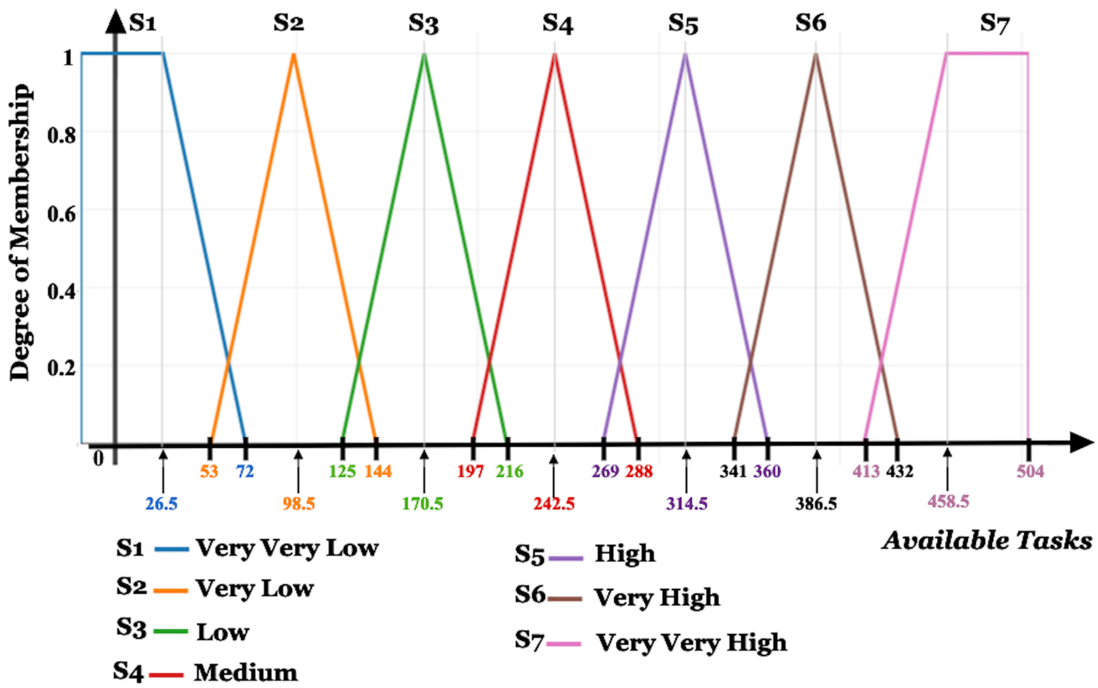

Figure 7.3. Membership functions for available tasks

In practice, the corresponding linguistic term labels the subset. However, this graphical representation helps to understand better the theoretical union of all subset to conform the whole fuzzy set A. It is noteworthy to point out that the described methodology allows creating programmatically equally spaced fuzzy sets that combine trapezoidal left shoulder, triangular, and trapezoidal right shoulder membership functions by merely employing the maximum value for the input/output vector and the corresponding substitutions in the Equations above (7.4), (7.7), (7.8), (7.9), and (7.10).

7.2.2 Extracting type-1 fuzzy rules from data

In the literature, it is accepted that a multiple-antecedent multiple-consequent rule can always be considered as a group of multi-input single-output rules [57]. As a result, it can be established that a type-1 FLS encompasses p inputs $x_1 \in X_1, \dots, x_p \in X_p$ with an output $y \in Y$. Furthermore, the fuzzy rules are generated by mapping the input data x^t and target outputs y^t over all N training, such as $(x^t; y^t)$ $T = \{1, .., N\}$. Consequently, a $l-th$ rule has the form [57]:

$$R^l: IF\ x_1\ is\ A_1^l and\ x_2\ is\ A_2^l\ and\ \dots and\ x_n\ is\ A_n^l\ THEN\ y\ is\ B^l \tag{7.32}$$

where $l = \{1, 2, \dots, R\}$, R is the total number of rules and l is the rule index, x_i are the inputs, A_i^l are the antecedents sets, i is the antecedent index $i = \{1, 2, \dots, n\}$, and n is the total of antecedents. The output is denoted by y and B^l are the consequent sets.

As demonstrated in Section 7.2.1, the characteristics of the data establish the centres of the fuzzy sets that appear in the antecedents and consequents of the rules. It is noteworthy to point out that the agile approach implemented allows a dynamic fuzzy system design. In other words, contrary to other approaches, this approach can be fed with different input/output vectors, and the system will be adjusted accordingly. This is an advantage towards entirely data-driven models, which do not have fixed rules nor fuzzy sets. As a result, the fuzzy system is flexible and suitable to tackle GDS problems.

7.3 Initial type-2 fuzzy logic system for GDS

Among the fuzzy community, it is currently accepted that the performance of fuzzy logic systems improves as one goes from crisp to type-1 and then to interval type-2 [172], [173] and [174]. In Chapter 3, a comprehensive revision of the differences between the different fuzzy systems was presented. This first incremental implementation under the agile modelling focuses on extending the type-1 membership functions developed in the previous section.

It is noteworthy to point out that the model stressed the use of characteristics of each input/output vector to generate its membership functions. This approach works for both a reduced number of linguistic labels and a large number of linguistic terms. Indeed, the procedure described in Section 7.2 implemented seven linguistic terms. However, for a reduced number of linguistic terms such as {*low, medium, high*} for a given input/output vector, the use of minimum, maximum, and mean of such vector are enough to find the data points of each membership function. Figure 7.4 illustrates this with a theoretical example.

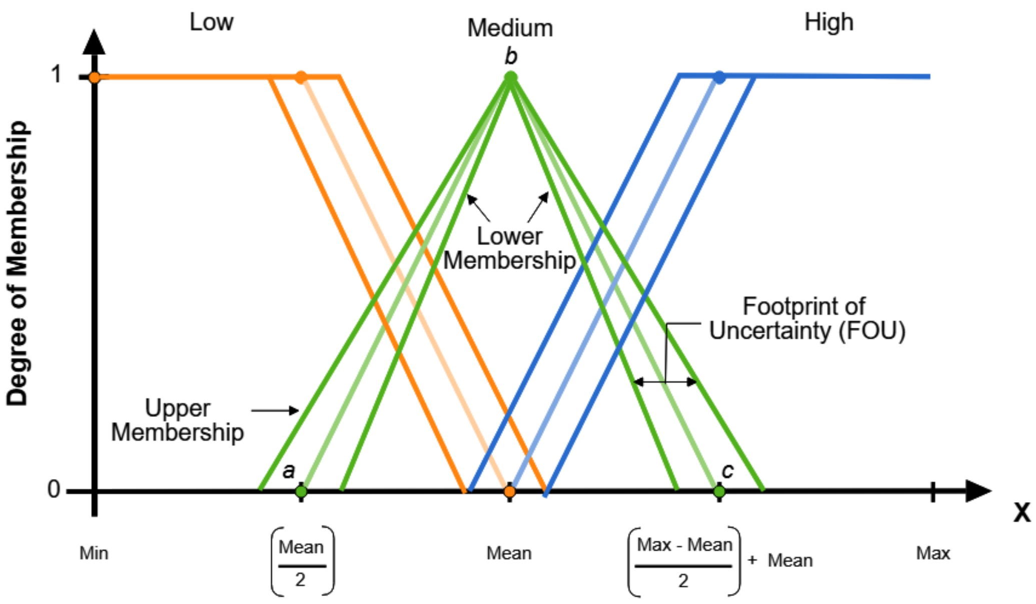

Figure 7.4. Membership functions using the minimum, maximum and mean values of a vector

However, the abovementioned example is acceptable for a small number of linguistic terms. Moreover, for a large number of linguistic terms, other approaches can be implemented. Consequently, the following subsection will detail the extension to type-2 membership functions based on their type-1 counterpart.

7.3.1 Construction of type-2 membership functions

The membership functions built in the type-1 FLS are defined as principal membership functions. To extend them to type-2 FLS, a bounded region that encompasses each principal membership function is incorporated by applying an uncertainty factor (ρ) to generate the Footprint of Uncertainty (FOU). This results in the generation of upper $\overline{\mu}_{\tilde{A}}(x)$ and lower membership $\underline{\mu}_{\tilde{A}}(x)$ functions. The coordinates of the upper membership function corresponding to the left and right point are at $(A - \rho)$ and $(B + \rho)$, respectively. Similarly, the coordinates of the lower membership function are at $(A + \rho)$ and $(B - \rho)$.

7.3.1.1 Demonstration of type-2 membership functions generation

To demonstrate the type-2 MF construction, Table 7.2 reports the whole set of coordinates for the type-2 MF generated from their type-1 counterpart. Where the column *label* lists the employed linguistic labels. Note that for brevity, each linguistic term has been shortened as follows: VVL = very very low; VL = very low; L = low; M = medium; H = high; VH = very high and VVH = very very high. The column *coordinates* reports the points to build the type-1 membership function as obtained in Section 7.2.1.1. Column (A) is the left coordinate for the primary MF. Column (B) is the right coordinate for the primary MF. Columns UMF and LMF report the coordinates obtained from the procedure mentioned above. Figure 7.5 depicts the visual representation of the resulting type-2 MFs.

Table 7.2– Values to demonstrate type-2 membership functions generation.

Label	Coordinates	(A)	(B)	Coordinates	
				UMF	LMF
VVL	[0, 0, 26.5, 72]	-	72	[-, 85]	[-, 58]
VL	[53, 98.5, 98.5, 144]	53	144	[39, 157]	[66, 130]
L	[125, 170.5, 170.5, 216]	125	216	[111, 229]	[138, 202]
M	[197, 242.5, 242.5, 288]	197	288	[183,301]	[210, 274]
H	[269, 314.5, 314.5, 360]	269	360	[255, 373]	[282,346]
VH	[341, 386.5, 386.5, 432]	341	432	[327, 445]	[354, 418]
VVH	[413, 458.5, 504, 504]	423	-	[409, -]	-

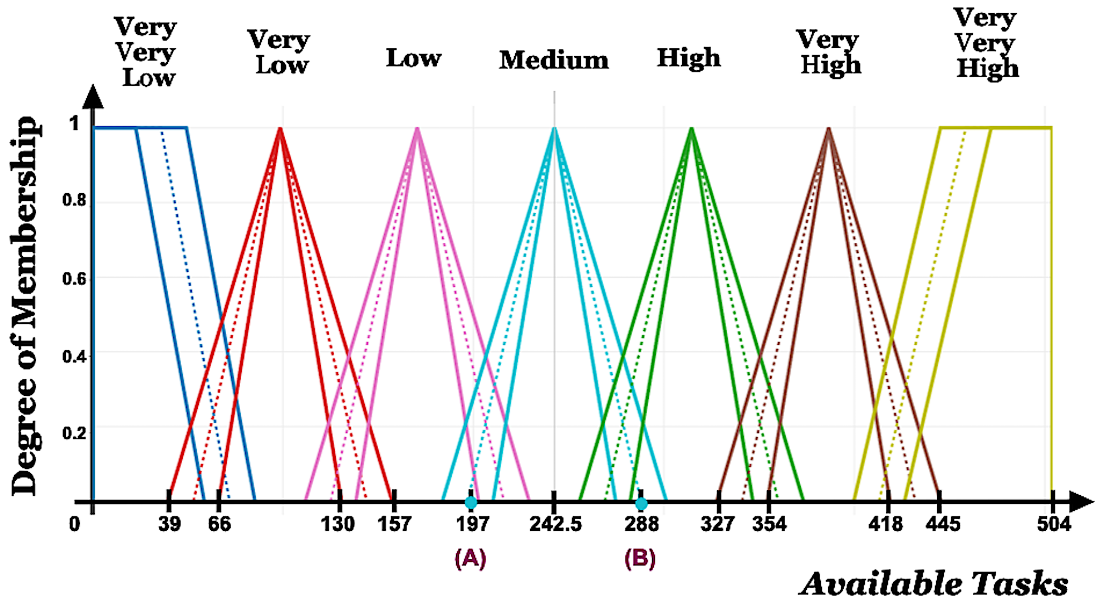

Figure 7.5. Type-2 MFs obtained from type-1 MFs

7.3.2 Extracting type-2 fuzzy rules from data

It is commonly accepted that the nature of the membership functions dictates the distinction between type-1 and type-2 FLSs. However, this is not relevant when conforming the rules [57]. Consequently, this enables that for type-2, the structure of the rules remains exactly the same as in type-1, with the only difference that now some or all the sets involved are type-2 [57].

These rules will be combined and will map the input type-2 fuzzy sets to output type-2 fuzzy sets and take the following form [34]:

$$R_l: IF\ x_1\ is\ \widetilde{A}_1^l\ \ldots and\ x_n\ is\ \widetilde{A}_n^l\ THEN\ \ y_1\ is\,\widetilde{B}_1^l \tag{7.33}$$

where $l = \{1, 2, \ldots, R\}$, R is the total number of rules and l is the rule index, x_i are the inputs, $\widetilde{A}_i^l$ are the antecedents sets, i is the antecedent index $i = \{1, 2, \ldots, n\}$, and n is the total of antecedents. The output is denoted by y and $\widetilde{B}^l$ are the consequent sets.

Successively, compute the upper $\overline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)$ and lower $\underline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)$ membership values and for each of the fuzzy set $\widetilde{A}_s^q, q = 1, \dots, V_i$, and for each input variable $(s = 1, \dots, n)$. Find $q^* \in \{1, \dots, V\}$ such satisfies [175]:

$$\mu_{\tilde{A}_s^{q*}}^{cg}\left(x_s^{(t)}\right) \geq \mu_{\tilde{A}_s^q}^{cg}\left(x_s^{(t)}\right) \tag{7.34}$$

For all $q = l, \dots, V_i$. Notably, $\mu_{\tilde{A}_s^q}^{cg}\left(x_s^{(t)}\right)$ is the centre of gravity of the interval membership of $\tilde{A}_s^q$ at $x_s^{(t)}$, it can be seen as follows [175]:

$$\mu_{\tilde{A}_s^q}^{cg}\left(x_s^{(t)}\right) = \frac{1}{2}\left[\overline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right) + \underline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)\right] \tag{7.35}$$

The following rule will be referred to as a rule generated by $(x^{(t)}; y^{(t)})$ and expressed as [175]:

$$IF x_1 is\ \tilde{A}_1^{q^{*(t)}} \dots and\ x_n\ is\ \tilde{A}_n^{q^{*(t)}} THEN\ y\ is\ centered\ at\ y^{(t)} \tag{7.36}$$

For all of the input variables x_s there are V_i type-2 fuzzy sets $\tilde{A}_s^q$, which enables the greater number of potential rules equal to V_i^n [57]. Therefore, resolving conflicting rules will involve computing the weighted average $(av^{(l)})$ for the conflicting group. Computing $av^{(l)}$ is expressed in Equation (7.44), where u=1,…,N and t_u^l is the data points index of the conflicting group l, w is the rule weight [175]:

$$av^{(l)} = \frac{\sum_{u=1}^{N_l} y^{(t_u^l)} wi^{(t_u^l)}}{\sum_{u=1}^{N_l} wi^{(t_u^l)}} \tag{7.37}$$

These N_l rules are combined into a single rule, utilising the following format [175]:

$$IF\ x_1 \text{is}\ \tilde{A}_1^l \ldots \text{and}\ x_n \text{is}\ \tilde{A}_n^l\ \text{THEN}\ y\ \text{is}\ \tilde{B}^l \tag{7.38}$$

where there is the selection of the output fuzzy set $\tilde{B}^l$ based on the following: amongst the V_o output interval type-2 fuzzy sets $\tilde{B}^l, \ldots, \tilde{B}^{V_o}$ find the B^{h*} such that [175]:

$$\mu_{\tilde{B}^{h*}}^{cg}\left(av^{(l)}\right) \geq \mu_{\tilde{B}^{h}}^{cg}\left(av^{(l)}\right) \ \text{ for } h = 1,2 \ldots, V_o \tag{7.39}$$

$\tilde{B}^l$ is selected owing to the fact that B^{h*}, where $\mu_{\tilde{B}^h}^{cg}$ is the centre of gravity of the interval membership of $\tilde{B}^h$ at $av^{(l)}$as in Equation (7.35).

7.4 Experiments for the initial type-1 and type-2 FLSs for GDS

The aim of this section is to provide the configuration of the required inputs to achieve specific goals within one geographical domain within the UK territory. As indicated in Section 6.2.1, the detailed names of the working areas are anonymised per compliance request. Due to the complexity inherent in field scheduling processes, a clear experiments settings definition is required. Therefore, let us review the following step-by-step set of conditions for these experiments.

First, a non-expert operational planner wants to generate a work plan for their workforce. The user is assisted by the analytical tool introduced in Section 6.3, which is part of the work presented in this thesis. It is worth to remember; that this analytical tool is not the BT's scheduler system. The scheduler is considered a black-box. The referred scheduler manages complex processes for task allocation while ensuring specific optimisation requirements. As mentioned in Section 2.1.5, this scheduler has been in development and continues improvements for nearly 20 years. Hence, the black-box approach.

Next, the operational planner identifies a daily profile of the demand, the business priorities, among other insightful information, and the number of allocated and unallocated tasks after conducting a simulation request. Generally, a simulation request corresponds to a specific day. At this point, the user does not know how to improve the job allocation, which is a high-level indicator of how the field service delivery will perform.

This is a perfect example of the "what-if?" scenario simulation analysis described in Section 5.1. Deliberately, if the simulation response is not aligned to the business targets, the user needs to run another simulation. However, at this time, the operational planner might try to adjust any input parameter and see whether the new results are suitable for their goals. This repetitive cycle is the trial-and-error concept itself. This is not ideal for productive real-world operations. There is another challenge, as pointed out at the beginning of this step-by-step walk-through; the user, in this case, is not an expert. Consequently, it can be appreciated the risk and difficulty to obtain feasible results. Hence, the need for GDS in this context.

To aid this situation, the proposed GDS approach, firstly, uses the data generated per the description of Section 6.2.1; and secondly, implements the conventional simulation described in Section 6.3. Then, a sub-set of the total number of scenarios represent the data set for training the type-1 and type-2

FLSs. And another sub-set for testing. Particularly 70% for the former and 30% for the later in these experiments.

In this example, decision-making relates to the portfolio configuration that meets specific business goals. Therefore, the type-1 and type-2 are trained with a 70% random selection of the synthetic data set that encompasses a global portfolio of 40,795 tasks. 56% (22,772) corresponding to repair work and 44% (18,023) to provision work. The total estimated duration for this sample is 323,023 hours across 131 different scenarios. At this stage, a scenario contains a series of metrics and characteristics that reflect a single result from a simulation request. As a result, “what-if?” simulation requests are now handled by the GDS approach; this releases users from time-consuming sessions trying to figure out an adequate resulting scenario.

For the experiments in this section, the type-1 and type-2 approaches attempt to provide a set of inputs that will enable the achievement of the goals described in Table 7.3. As can be observed, the percentage value is set to a constant for each goal. This to reflect common request in real-world situations. One could anticipate that everyone would like to achieve 100% as a target; however, often, these expectations get affected by unforeseen circumstances. As a result, feasible targets are preferred instead.

Each business target being evaluated, as indicated in Table 7.3. These initial experiments were conducted in two stages. Firstly, training and the next testing. The different levels of FOU were adjusted empirically. Performance is given by the accuracy achieved through the results. This accuracy is measured according to the root mean square error (RMSE) as follows:

$$RMSE_{output} = \sqrt{\frac{\sum_{i=1}^{N}(P_i - A_i)^2}{N}} \qquad (7.40)$$

Table 7.3– Business objectives supported in initial GDS approach experimentations.

Goal	Business Goal Description
1	How to schedule 99% of tasks
2	How to achieve a success rate of 97% for Provision Appointments
3	How to utilise 99% of the workforce
4	How to achieve a success rate of 97% for Repair Appointments

7.4.1 Inputs and outputs identification

Each goal requires specific inputs and outputs. Table 7.4 reports a comprehensive list of each relevant attribute in the achievement of the desired goals and their role in the fuzzy learning process. Where the column *I* denotes an input that is fed into the FLS, and it will conform to the antecedent part of the fuzzy rules. Similarly, the column *O* denotes an output that will be part of the consequent part of the fuzzy rules. The columns *Goal 1*, *Goal 2*, *Goal 3* and *Goal 4* refer to the abovementioned goals introduced in Table 7.3 and indicate the relevance of each attribute for each desired target. In other words, whether the attribute is used in goals 1, 2, 3 and 4, respectively. The column *Description* provides the name of the attribute being employed. Similarly, the column *Abbreviation* indicates the short form of each attribute.

Table 7.4– Distinction between inputs and outputs (Š is an output in Goal 4).

Abbreviation	Description	I	O	Goal 1	Goal 2	Goal 3	Goal 4
R_i	Available resources	●	●Š	●	●	●	●
J_i	Available jobs	●		●	●	●	●
WT_i	Available working time	●		●			
MHA_i	Man-hours available		●			●	
$MSRA_i$	Multi-skilled resources allocated		●		●	●	
PJS_i	Percentage of jobs scheduled	●		●			
$\mathrm{PRU_i}$	Percentage of resource utilisation	●				●	
PAS_i	Provision appointment scheduled		●	●	●		
PNS_i	Provision non-appointment scheduled		●	●	●		
$PPAS_i$	Percentage of provision appointment success	●			●		
$PRAS_i$	Percentage of repair appointment success	●					●
RAS_i	Repair appointment scheduled		●	●			●
RNS_i	Repair non-appointment scheduled		●	●			
$SSRA_i$	Single skilled resources allocated		●			●	

7.4.2 Type-1 and type-2 MFs

As introduced in Section 7.3, this first version of the FLS employs seven linguistic labels. To facilitate their readability, let us assign abbreviations to the linguistic values as follows {*very very low* = VVL, *very low* = VL, *low* = L, *medium* = M, *high* = H, *very high* = VH, *very very high* = VVH}.

The automatic construction of type-1 and type-2 membership functions was demonstrated in sections 7.2.1.1 and 7.3.1.1, respectively. This showcased that finding the coordinates for the primary memberships, the UMFs and the LMFs was reduced to simply substitution. This is relevant and highly practical for cases where the inputs and outputs vary according to each goal being sought.

Type-1 and type-2 MFs are computed for all the parameters reported in Table 7.4. For brevity and in order to showcase this construction, Table 7.5 provides an example of the coordinates for the construction of type-1 and type-2 membership functions for the parameter *available resources* R_i. Where the column *F* denotes the fuzzy set being computed. *Max* reports the maximum value from the data in the R_i parameter. *T* reports the aforementioned seven linguistic terms. The column *Coordinates* reports the points [a, b, c, d] to build the type-1 membership function. Column (A) is the left coordinate for the primary MF. Column (B) is the right coordinate for the primary MF. Columns *UMF* and *LMF* report the coordinates for the upper and lower membership functions, respectively. Figure 7.6 depicts the visual representation of the resulting type-1 and type-2 MFs for the aforementioned R_i parameter.

Table 7.5– MFs coordinates for the available resources R_I parameter.

F	Max	T	Coordinates	(A)	(B)	Coordinates UMF	Coordinates LMF
R_i	145	VVL	[0, 0, 0.92857, 20.8571]	-	20.8571	[0, 0, 0, 25.8571]	[0, 0, 0, 15.8571]
		VL	[1.85174, 21.7857, 21.7857, 41.7143]	1.85714	41.7143	[0, 21.7857, 21.7857, 46.7143]	[6.85714, 21.7857, 21.7857, 36.7143]
		L	[22.7143, 42.6429, 42.6429, 62.5714]	22.7143	62.5714	[17.7143, 42.6429, 42.6429, 67.5714]	[27.7143, 42.6429, 42.6429, 57.5714]
		M	[43.5714, 63.5, 63.5, 83.4286]	43.5714	83.4286	[38.5714, 63.5, 63.5, 88.4286]	[48.5714, 63.5, 63.5, 78.4286]
		H	[64.4286, 84.3571, 84.3571, 104.286]	64.4286	104.286	[59.4286, 84.3571, 84.3571, 109.286]	[69.4286, 84.3571, 84.3571, 99.286]
		VH	[85.2857, 105.214, 105.214, 125.143]	85.2857	125.143	[80.2857, 105.214, 105.214, 130.143]	[90.2857, 105.214, 105.214, 120.143]
		VVH	[106.143, 126.071, 504, 504]	106.143	504	[341, 121.071, 146, 146]	[111.143, 131.071, 146, 146]

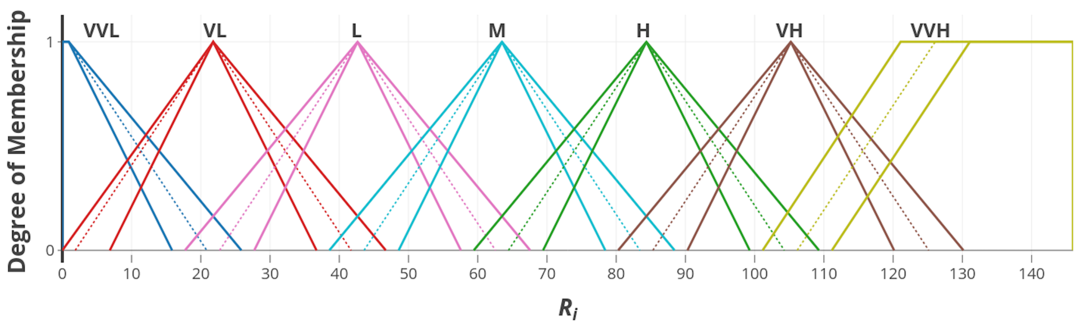

Figure 7.6. Membership functions for the available resources R_I parameter

7.4.3 Fuzzy rules

The fuzzy rules are generated per the procedure described in sections 7.2.2 and 7.3.2. It is worth to point out that the goal-driven nature of the problem requires a rule base for each desired goal. In other words, each goal has its own relevant parameters, as showcased in Table 7.4. The agile modelling approach being implemented provides flexibility; therefore, the model creates a new knowledge base with the corresponding inputs/outputs for each business goal. Therefore, Figure 7.7 depicts the fusion of type-1 and type-2 FLSs with the flow followed in the training and testing phases of these experiments.

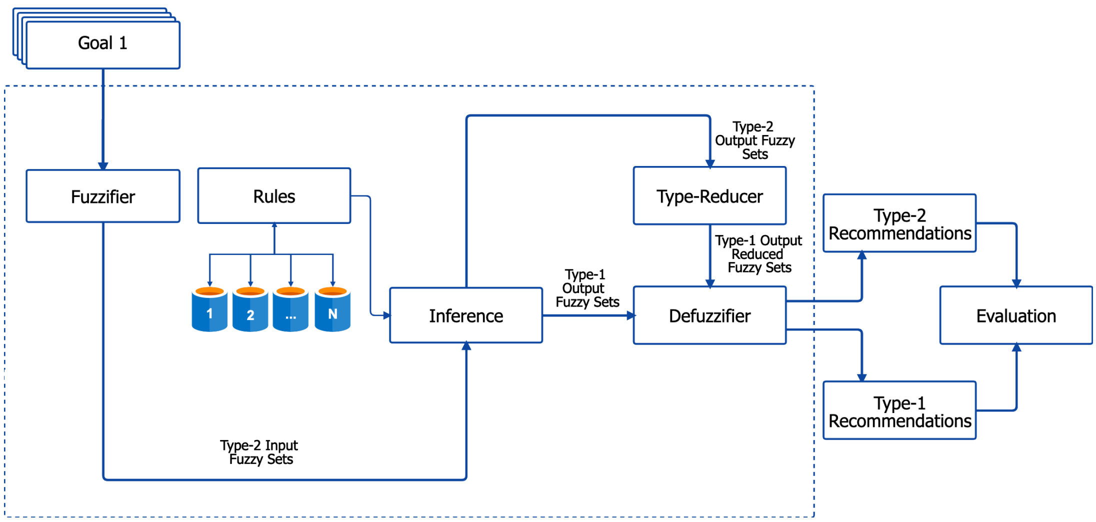

Figure 7.7. Fusion of type-1 and type-2 FLSs with their flow

It is clear that each goal has different input/output configuration requirements. Therefore, there are four rule bases for these experiments. For brevity, a subset of the rule base for Goal 1, Goal 2, Goal 3 and Goal 4 is reported in Table 7.6, Table 7.7, Table 7.8 and Table 7.9, respectively. Where the rule *index column* reports the index of the rule. The abbreviated antecedents in the

IF header represent the input parameters as detailed in Table 7.4. Similarly, the abbreviated consequents in the *THEN* header represent the output parameters previously detailed in Table 7.4.

A brief description of the aforementioned tables can be summarised as follows: the rule base for Goal 1 encompasses 842 rules after removing conflicting rules. Analogously, for Goal 2, the rule base has a total of size of 223 rules after removing conflicting rules. Similarly, the required rules for Goal 3 are 188 rules after removing conflicting rules. Finally, 31 rules are related to the configuration of Goal 4 after removing conflicting rules.

Table 7.6– Extract of rule base for Goal 1, from a total size of 842 rules.

Rule Index	IF Antecedents				THEN Consequents			
	R_i	J_i	WT_i	PJS_i	PAS_i	PNS_i	RAS_i	RNS_i
1	VVL	VVL	VVL	VVL	VVL	VVL	VVL	VVL
85	VVL	VL	VL	VL	VL	VL	L	L
125	VVL	L	VL	L	L	VL	M	M
280	VL	VL	M	M	L	L	H	VL
325	L	M	M	L	M	M	H	M
380	M	L	VL	H	M	H	L	M
405	M	M	H	VH	M	L	M	VH
480	H	M	H	VH	M	VL	H	VH
550	H	H	VH	L	L	H	M	M
670	H	VH	L	VH	M	L	H	VH
520	H	M	H	VH	L	M	H	H
680	VH	H	M	L	M	H	H	L
710	VH	H	H	H	H	L	L	H
790	VH	VH	VH	L	VVH	VVH	VVH	H
842	VVH	VVH	VVH	VVH	M	H	VH	L

Table 7.7– Extract of rule base for Goal 2, from a total size of 223 rules.

Rule Index	IF Antecedents			THEN Consequents		
	R_i	J_i	$PPAS_i$	PAS_i	PNS_i	$MSRA_i$
45	VVL	VL	VVL	L	M	VVL
63	VVL	VL	VL	VL	VL	L
81	L	L	VL	L	VL	M
95	L	VL	M	L	L	H
103	L	M	M	M	M	H
115	M	L	VL	M	H	L
126	M	L	H	M	L	M
131	H	M	H	M	VL	H
132	H	H	VH	L	H	M
143	H	VH	L	M	L	H
148	H	M	H	L	M	H
150	VH	H	M	M	H	H
198	VH	H	H	H	L	L
201	VH	VH	VH	VVH	VH	VVH
202	VVH	VVH	H	M	H	VH

Table 7.8– Extract of rule base for Goal 3, from a total size of 188 rules.

Rule Index	IF Antecedents			THEN Consequents		
	R_i	J_i	PRU_i	MHA_i	$SSRA_i$	$MSRA_i$
16	VVL	VL	L	L	M	VVL
33	VL	VL	L	L	M	L
59	L	M	VL	L	VL	M
67	L	VL	M	L	L	H
70	L	M	M	M	M	H
78	M	M	VL	M	H	L
87	M	L	H	M	L	M
95	H	M	H	M	VL	H
124	H	H	VH	L	H	M
131	H	M	M	M	H	H
156	H	M	H	H	M	H
160	VVH	VH	M	VH	H	H
161	VVH	VH	H	VH	H	VH
170	VVH	VH	VH	VVH	VH	VVH
176	VVH	VVH	VVH	VVH	VL	VH

Table 7.9– Fuzzy rule base for Goal 4.

Rule Index	IF Antecedents		THEN Consequents	
	J_i	$PRAS_i$	RAS_i	R_i
1	VL	VVL	M	VL
2	L	VVL	H	L
3	M	VVL	VH	M
4	H	VVL	VVH	H
5	VVH	VVL	VL	VVH
6	VL	VL	M	VL
7	H	VL	VVH	H
8	VH	VL	VVL	VH
9	VVH	VL	VL	VVH
10	VVL	L	L	VVL
11	VL	L	M	VL
12	L	L	H	L
13	M	L	VH	M
14	H	L	VVH	H
15	VH	L	VVL	VH
16	VVH	L	VL	VVH
17	VL	M	M	VL
18	L	M	H	L
19	M	M	VH	M
20	H	M	VVH	H
21	VVH	M	VL	VVH
22	L	H	H	L
23	H	H	VVH	H
24	VVL	VH	L	VVL
25	L	VH	H	L
26	VH	VH	VVL	VH
27	VVH	VH	VL	VVH
28	L	VVH	H	L
29	M	VVH	VH	M
30	VH	VVH	VH	VH
31	VVH	VVH	VVH	VVH

7.4.4 Results

Each of the learning and testing phases for every goal encompassed 1,000 evaluation cycles. These experiments were executed in a virtual machine (VM) with a 64-bit processor at 1.7 GHz quad-core and a maximum of 8 GB total available random-access memory (RAM). Figure 7.8 and Figure 7.9 depict the distribution of time in milliseconds for all the goals being sought in these experiments. As can be observed, the size of the rule base and the type of FLS influenced the total average time expended to compute the training and learning phases in each goal. Overall, the average time is higher in the type-2 FLSs. Among all cases, the system with more rules took more time. This is Goal 1 with a rule base of 842 items (for a subset example of the rule base, see Table 7.6). Similarly, in Goal 4, the small number of rules resulted in a lower time.

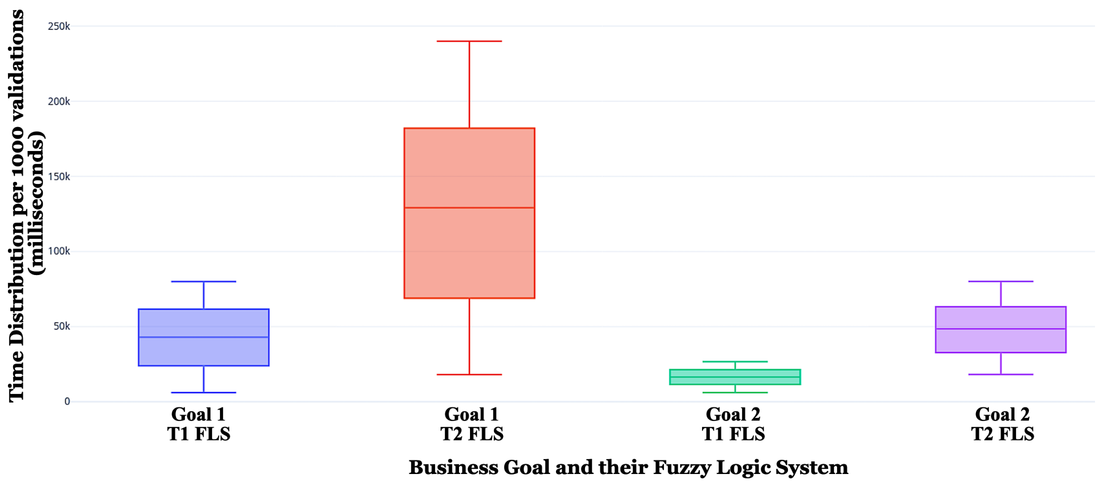

Figure 7.8. Time distribution for learning and testing in Goals 1 and 2

In practice, this finding has low impact and limited relevance. This mainly because in the modern deployment era, the use of containers allows load balancing and scalability out of the box. Therefore, these execution times do not bring any issue for modern practices. However, this information may be useful for companies that still use virtualised or traditional deployments. Their differences can be listed as follows: in traditional deployments, applications ran on physical servers; in virtualised deployments, applications can be executed in multiple Virtual Machines (VMs) on a single physical server's CPU. In contrast with their traditional and virtualised counterpart, containers are lightweight as they are decoupled from the underlying infrastructure and Operating Systems (OSs). As a result, containers enable entire runtime environments that are portable across clouds and OS distributions [176].

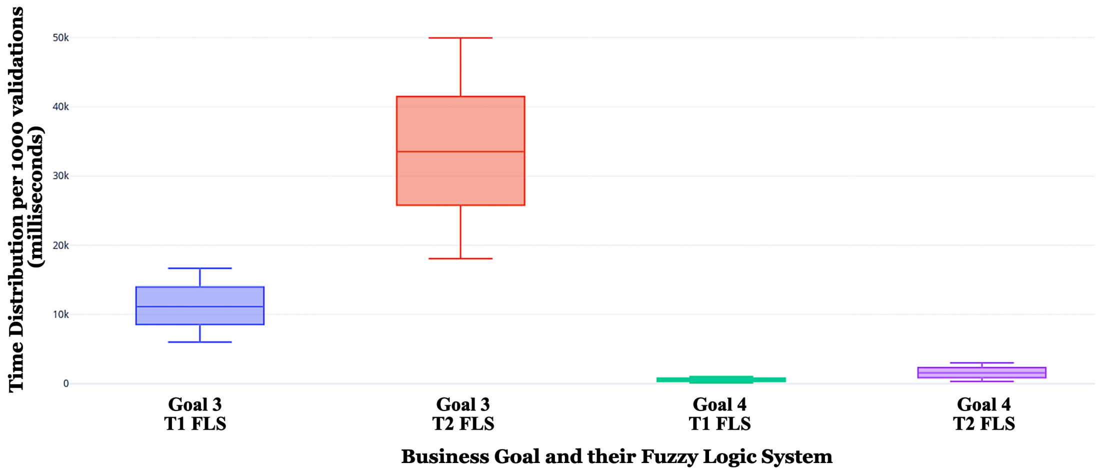

Figure 7.9. Time distribution for learning and testing in Goals 3 and 4

As indicated in Equation (7.40), the root mean square error (RMSE) is employed to evaluate the obtained results. The closer the RMSE is to zero, the better the performance in the experiments. In the other hand, the further away from zero, the worst the performance. Table 7.10 reports the obtained results for each goal.

Table 7.10– RMSE comparison between type-1 and type-2 FLS for all goals.

Goal	Training		Testing	
	Type-1	Type-2	Type-1	Type-2
1	0.8522452	0.6746846	0.7928875	0.6520265
2	0.5730032	0.2959931	0.5715524	0.2952001
3	0.7277007	0.5222968	0.6043349	0.4430870
4	0.3524441	0.2802045	0.3183252	0.2765011
Average	**0.6263483**	**0.44329475**	**0.5717750**	**0.4167036**

With regard to Goal 1, it can be observed that in the training phase, the type-2 FLS outperformed its counterpart type-1 FLS by 20%. Similarly, in the testing phase, the type-2 FLS kept the same tendency with 17% better performance than the type-1 counterpart. With respect to Goal 2, in the training and testing phases, the type-2 FLS outperformed its counterpart type-1 FLS by 48%. A similar tendency is observed in Goal 3, wherein the training and testing phases, the type-2 FLS outperformed its counterpart type-1 FLS by 28% and 26%, respectively. When focussing on Goal 4, in the training and testing phases, the type-2 FLS outperformed its counterpart type-1 FLS by 20% and 13%, respectively.

Unsurprisingly, on average, the type-2 FLS outperformed its counterpart type-1 FLS by 29% in training. Similarly, in the testing phase, the type-2 FLS kept the same tendency with 27% better performance than the type-1 counterpart. The relevance of these experiments is that agile fuzzy modelling has enabled the achievement of goals with sensible results. This enables target-oriented management, avoiding the time-consuming trial-and-error approach.

The following subsection will review the benefits of these initial version in detail.

7.5 Benefits of the initial type-1 and type-2 versions for GDS

Firstly, the GDS problem is approached incrementally. This means that the problem has been modelled with the minimum inputs and outputs that conform to a portfolio configuration to achieve certain goals. Additionally, conventional simulated data has been embedded successfully to model the fuzzy system.

At this stage, the basis for a structured end-to-end framework has been achieved; this includes a concise strategy for data collection, an automated method for fuzzy modelling and the capability to handle multiple goals. In practice, the benefits of the proposed approach for the developed experiments can be listed as follows:

1) Users can determine the portfolio configuration to achieve defined business goals in a simple way that does not suffer from trial-and-error shortcomings. To better understand this benefit, Figure 7.10 depicts the differences between the traditional and this target-oriented approach. As can be observed, the user now can find a suitable configuration for the first time, which is invaluable in tight schedules and heavy workloads where saving time improves productivity drastically.

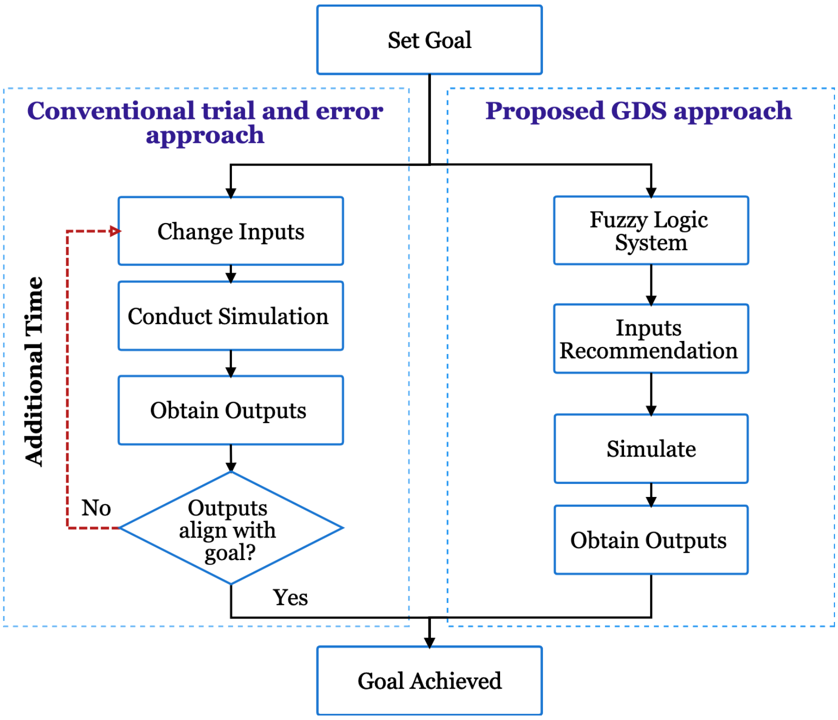

Figure 7.10. Comparison between trial-and-error simulation vs GDS

2) The model is suitable for multiple goals. As demonstrated in this chapter, the proposed approach was tested with four goals. This capability is not clearly formalised in conventional approaches. Hence, the immediate benefit of this proposal.
3) The results are obtained within an acceptable time frame. Contrary to conventional approaches where the time expended can go exponentially due to their trial-and-error nature, in the proposed GDS, the time to achieve a specific goal is limited by the amount of data involved in a particular business target. For example, with the setup described in this chapter, the maximum clocked time was 4 minutes (see the box plot for Goal 2: Type-2 FLS reported in Figure 7.8).
4) Users benefit from accessing the underlying rule base; this encouraged discussion and consensus between expert and non-expert users.

Contrary to advanced heuristic search, or multi-objective genetic algorithms, this approach allowed users to follow, discuss and understand the strategy for data collection, the automated method for fuzzy modelling and the capability to handle multiple goals.

7.6 Discussion

This chapter has introduced the concept of agile modelling in the context of fuzzy logic systems development. Successively, this chapter walked the reader through the construction of the initial type-1 FLS for GDS by reviewing the type-1 MFs construction and providing a detailed demonstration of an approach for their automatic MFs generation. Subsequently, this chapter reviewed the fuzzy rules extraction from data. Next, it presented the construction of the initial type-2 FLS, which extended its type-1 FLS counterpart. Then, this chapter reviewed the type-2 MFs construction and provided a detailed demonstration of this construction. Successively, it reviewed the method for type-2 fuzzy rules extraction from data. After that, this chapter described the setup for the experiments carried out in these initial versions. Successively, this chapter identified the inputs and outputs and illustrated the MFs generation, and it reported the fuzzy rules for each goal being sought. Finally, this chapter reported the results and provided a review of the benefits achieved at this stage.

Each section of this chapter has devoted to providing a detailed insight into the methodology implemented in the use of fuzzy logic for human-understandable problem-solving. To recapitulate, AM allows focusing on modelling rather than in software development. This is important because AM enables a series of benefits such as the ability to grow incrementally, the flexibility to incorporate changes along the path of modelling, and the focus on modelling with a purpose, which allows to centre efforts on certain targets.

Moreover, a conventional simulation was embedded in the GDS model by incorporating their traditional simulated scenarios, which contributed towards a concise strategy for data collection, an automated method for fuzzy modelling and the capability to handle multiple goals. This allowed the construction of type-1 and type-2 FLSs. The fusion of these architectures resulted in an efficient composite flow that enabled a transparent end-to-end execution of the experiments and a fast evaluation.

Each goal presented its review of the results. The RMSE was used as a metric for performance. As shown in Table 7.10, on average, the type-2 FLS outperformed its counterpart type-1 FLS by 29% in training. Similarly, in the testing phase, the type-2 FLS kept the same tendency with 27%.

The main benefits of this stage were reviewed. These benefits included: (1) the ability to determine the portfolio configuration to achieve certain business goals in a simple way that does not suffer from trial-and-error shortcomings, (2) the suitability for handling multiple goals, (3) the capacity to generate sensible results within a sensible time frame, and (4) the reveal of the underlying modelling to users powered fully by data.

While these results are encouraging, some shortcomings were identified. Namely, the FLSs removed the conflicting rules by computing the weighted average for the conflicting group; this was effective to prevent our model from rule explosion. However, considering that the number of inputs and outputs were limited, another method more efficient needs to be employed. Similarly, the FOU was calculated empirically. Therefore, an optimised and automatic approach needs to be considered. These shortcomings will be addressed in Chapter 9.

Additionally, the presented FLSs employed equally spaced trapezoidal left shoulder, triangular, and trapezoidal right shoulder fuzzy sets by employing an automation method based on the maximum value for each input/output vector, which is acceptable. However, the data acquisition process allows us to calculate other data characteristics, such as mean or standard deviation. Consequently, another shape can be easily implemented. Finally, the number of linguistic variables was considerable high (i.e. seven different linguistic labels). It is worth to experiment with a smaller number of terms because explainability should improve with a smaller number of terms. These topics will be addressed in Chapter 8.

Overall, the work presented in this chapter is a solid foundation to increase features to the model incrementally; each presented section addressed a specific block for building the GDS approach. The following chapter will focus on increasing complexity and strengthen the model by introducing fuzzy clustering techniques, employing different shapes for the MFs and reducing the number of linguistic terms. Similarly, the next chapter will introduce strategies for input and output selection based on fuzzy correlation analysis and similarity analysis.

Chapter 8 - Uncertainty and the Type-2 Fuzzy Logic System for Goal-Driven Simulation

This chapter focuses in enhancing the initial version of the type-2 FLS developed in the previous chapter by adding relevant features to the model such as the use of a fuzzy clustering method, the implementation of Gaussian MFs, defining a strategy to analyse the correlation of inputs and outputs based on fuzzy correlation analysis and implementing a strategy to address misclassification cases based on similarity analysis.

Experiments employ higher data volume in comparison with the experiments carried out in the previous chapter. On average, the results show that the enhanced T2 FLS outperforms its previous version by 10% and 1% in the training and testing phases, respectively. A benchmarking assessment against opaque box models employed shallow neural networks. The results for training show that better performance is obtained by the ANN, on average. The shallow ANN outperforms its counterpart T1 FLS, T2 FLS (initial versions), and T2 FLS (enhanced version) by 49%, 39% and 32%, respectively. Similarly, in testing, the shallow ANN outperforms its counterpart T1 FLS, T2 FLS (initial version), and T2 FLS (enhanced version) by 50%, 41% and 40%, respectively.

However, the lack of explainability in the shallow ANN demonstrated the unsuitability of black-box approaches to integrate scalable operational frameworks.

8.1 Type-1 MFs clustering

Clustering algorithms focus on grouping related items. Clustering techniques allow addressing one of the shortcomings of the FLSs introduced in the previous chapter, namely the use of equally spaced membership functions. Therefore, based on clustering classification, the type-1 membership functions (T1MFs) are obtained. The aim is to associate each data observation to all possible valid clusters within a membership value.

For the purposes of this thesis, the fuzzy c-means algorithm (FCM) is employed. Overall, the FCM algorithm carries out an iterative optimisation based on the number of clusters and the degree of fuzzy overlap m [177] and [178]. Figure 8.1 depicts each step of this iteration, which can be summarised as follows: firstly, random initialisation of the cluster membership value. Thereafter, compute the cluster centroid C_j of the j^{th} cluster. Next, for each cluster k in the total defined clusters K, update the degree of membership μ_{ij}. Then, compute the objective function. Successively, if the objective function has reached a certain threshold value or maximum iteration parameter, then it stops. Otherwise, return and iterate from the computation of the cluster centroid step. Additional details of fuzzy set-based clustering can be found in [179] and [180].

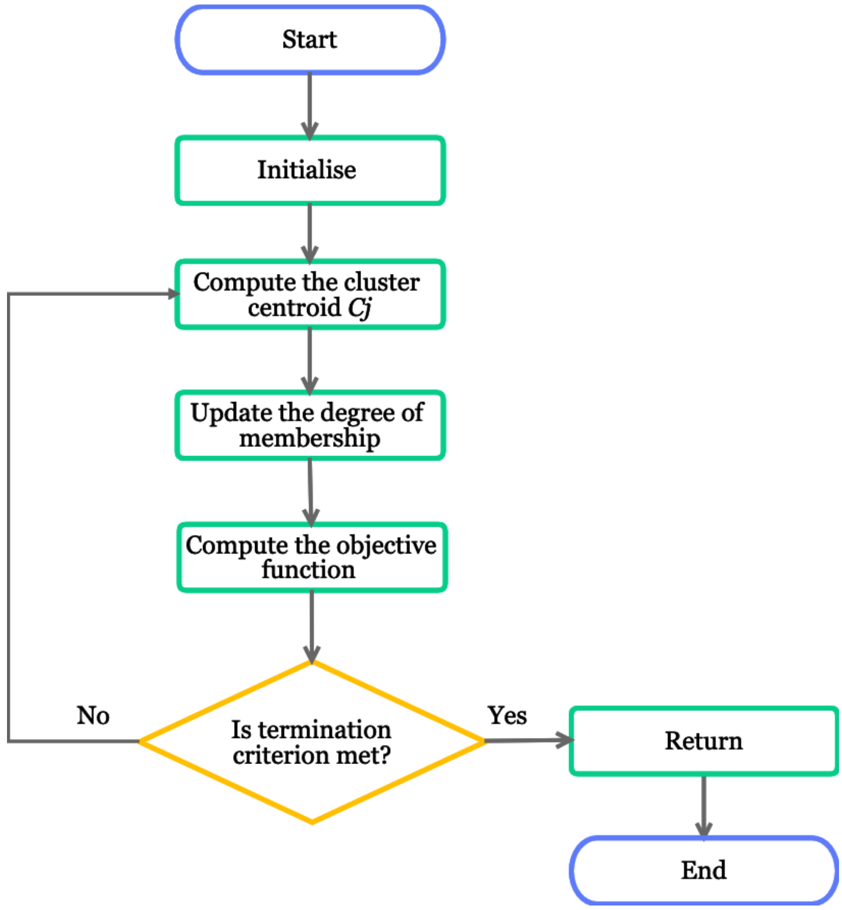

Figure 8.1. FCM clustering algorithm iterative flow (Source: [180])

For this incremental version being presented, the degree of fuzzy overlap m is set empirically. Additionally, another opportunity for improvement in the FLSs introduced in the previous chapter related to the high number of linguistic labels. In the initial FLSs versions seven linguistic terms were employed. However, a smaller number of linguistic terms will result in better interpretability. Hence, for this version, three linguistic labels will be used. Namely, *low*, *medium* and *high*.

In this version, membership functions continue their generation based on the data characteristics approach. In this context, trapezoidal left shoulder, triangular, and trapezoidal right shoulder were employed in the previous chapter. However, for this new version, Gaussian MFs will be employed. It is generally accepted that Gaussian MFs have reduced complexity. This mainly because only two parameters are required for their construction. Namely, the mean and the standard deviation [181], let us denote the mean by c and the standard deviation with σ. Consequently, a Gaussian membership function is given by [181]:

$$f(x;\ \sigma,\ c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{8.1}$$

8.1.1 Demonstration of Gaussian type-1 membership functions generation

The abovementioned principles for T1MFs generation can be demonstrated in a fourfold step procedure. First, all the available input/output vectors are clustered by the above detailed FCM algorithm with a predefined number of clusters equal to three. Namely, *low*, *medium* and *high*. Second, for each resulting cluster C_j log the mean and the standard deviation. Third, for each input/output vector parameter generate the corresponding Gaussian MFs for each of their three computed clusters. Fourth, integrate the full fuzzy set A for each input/output vector by collecting all points $x \in X$ with their associated membership function $\mu_A(x)$ as follows [171]:

$$\forall x \in X :\ \mu_{\dot{\cup}_{t \in T} C_j}(x) = \textstyle\sum_{t \in T} \mu_{C_J}(x) \tag{8.2}$$

where C_j denotes a clustered subset for a t linguistic term. A linguistic term is denoted by $t = \{1, 2, 3\}$. Formally, T represents the total number of linguistic terms, in this case, this was set up to three. However, the same principle works for higher number of terms. The theoretic operation of union is denoted by $\sum$. Figure 8.2 depicts this workflow, which after processing all input/output vectors returns all composite fuzzy sets.

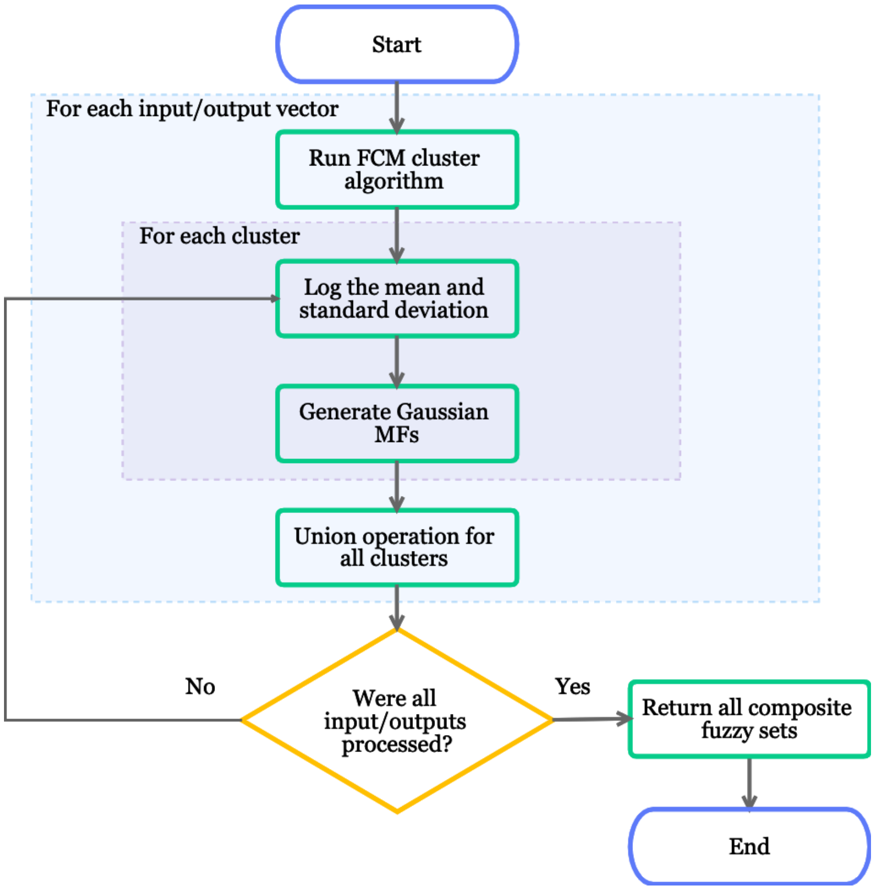

Figure 8.2. Gaussian T1MF generation

The first and second steps of the abovementioned workflow are now demonstrated with the following configuration: N number of total clusters equal to three, a degree of fuzzy overlap $m = 5.0$, the stop criteria ε encompassing a maximum number of iterations equal to 100 and an improvement in the objective function between two consecutive iterations $max_{\,ij}\{|\mu_{ij}^{k+1} - \mu_{ij}^{k}|\} < 0.03$. For brevity, Table 8.1 reports the results for a subset of the input/output vectors available in the GDS problem. Where the column headers detail the mean c for each cluster and the corresponding standard deviation σ. Column F reports the nomenclature for each parameter and the column *Description* provides the name of such vector.

The third step instructs to generate the corresponding Gaussian MFs for each of their three computed clusters. For example, in the case of the number of locations visited which is denoted by LV_i, the reported mean is 28.53 and the corresponding standard deviation is 16.81 for the linguistic label $\{low\}$. Therefore, Figure 8.3 depicts the resulting Gaussian MF per Equation (8.1).

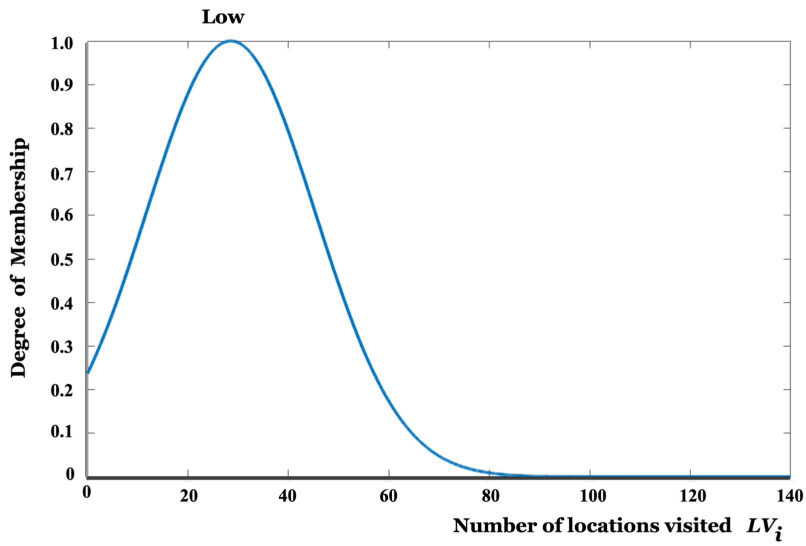

Figure 8.3. Gaussian T1MF for the linguistic term $\{low\}$ in the vector number of locations visited LV_i

Similarly, the LV_i vector reports mean values of 95.39 and 108.89 with their corresponding standard deviation values of 5.08 and 3.84 for the linguistic labels $\{medium\}$ and $\{high\}$, respectively. The resulting Gaussian MFs obtaining from applying Equation (8.1) are depicted in Figure 8.4 and Figure 8.5, respectively.

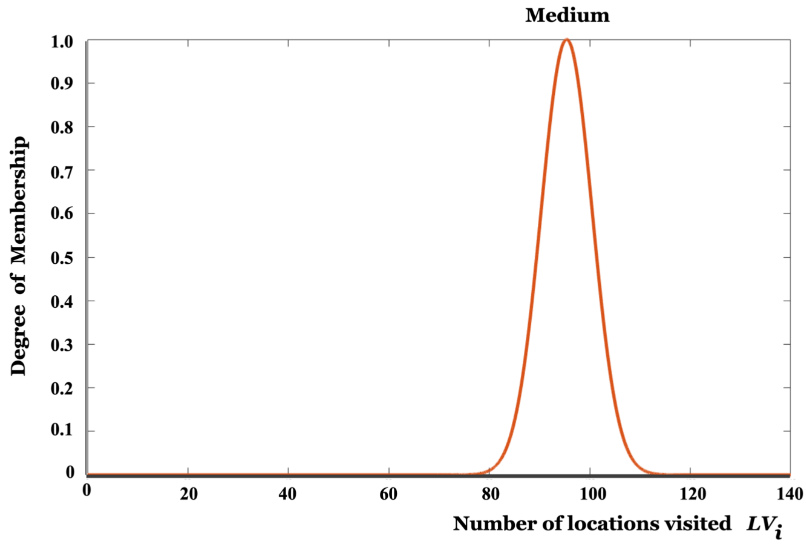

Figure 8.4. Gaussian T1MF for the linguistic term {*medium*} in the vector number of locations visited LV_i

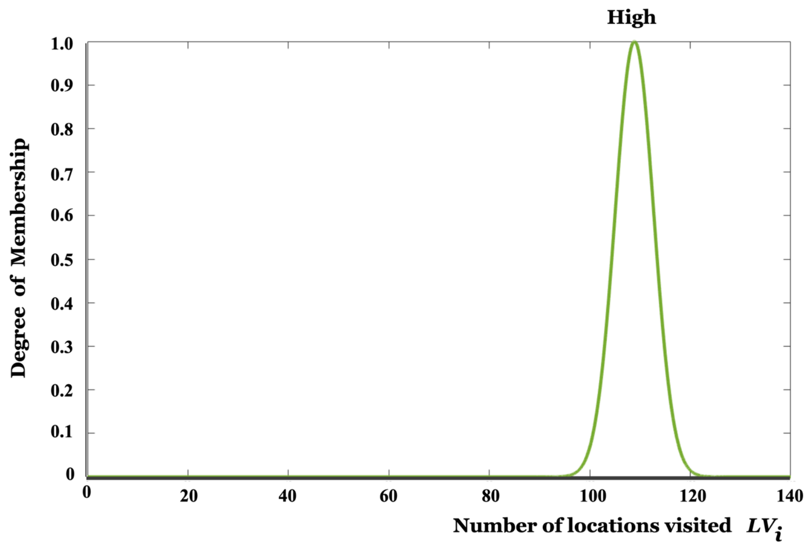

Figure 8.5. Gaussian T1MF for the linguistic term {*high*} in the vector number of locations visited LV_i

Finally, the theoretical union that integrates the full fuzzy set with the Gaussian MFs is obtained, as stated in Equation (8.2). For brevity, selected

Gaussian MFs for the abovementioned input/output vectors are depicted in Figure 8.6 and Figure 8.7.

Table 8.1– Values to demonstrate Gaussian T1MFs generation.

F	Description	Low		Medium		High	
		c	σ	c	σ	c	σ
R_i	Available resources	25.90	9.77	106.76	2.98	118.80	4.40
J_i	Available tasks	57.49	28.53	366.64	31.02	486.67	51.37
TTH_i	Actual total travel hours spent	20.23	13.17	106.91	13.68	150.74	13.25
TJH_i	Actual total task hours spent	64.80	39.78	409.37	33.40	521.09	27.78
TPA_i	Actual total provision appointment	4.36	7.62	100.76	17.83	156.05	23.30
MHA_i	Man-hours allocated	16.10	12.16	209.40	39.58	917.68	56.90
MH_i	Man-hours available	1.01	85.80	220.80	27.01	908.87	38.39
LV_i	Number of locations visited	28.53	16.81	95.39	5.08	108.89	3.84
RJ_i	Number of resources with job	2.06	1.49	24.67	4.78	108.30	6.77
ST_i	Number of scheduled tasks	49.99	30.46	290.59	34.32	387.70	36.04
PA_i	Provision appointment success	3.32	16.16	93.08	16.16	134.88	16.94
PNA_i	Provision non-appointment success	2.67	7.70	44.47	11.44	104.58	15.54
PAF_i	Provision appointment failure	1	1.70	13.63	4.55	38.13	10.89
$PNAF_i$	Provision non-appointment failure	1	1.70	13.63	4.55	38.13	10.89
RA_i	Repair appointment success	25.36	14.28	128.19	10.35	162.28	9.27
RNA_i	Repair non-appointment success	3.62	12.06	61.41	13.18	102.20	14.59
WHA_i	Work-hours available	9.05	36.74	76.34	68.34	541.40	1.54

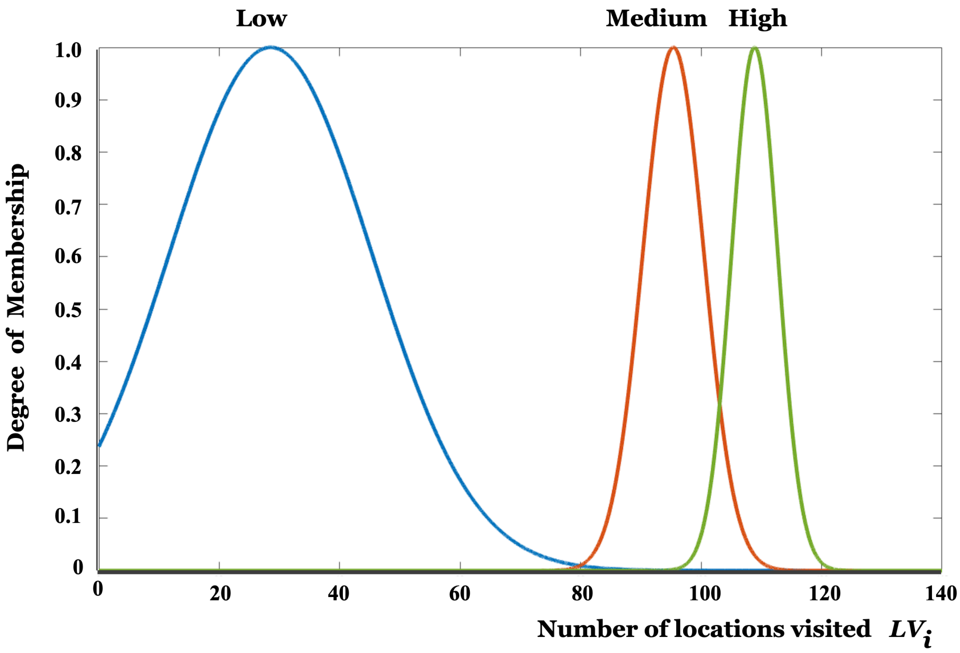

Figure 8.6. Gaussian T1MFs for the number of locations visited LV_i parameter

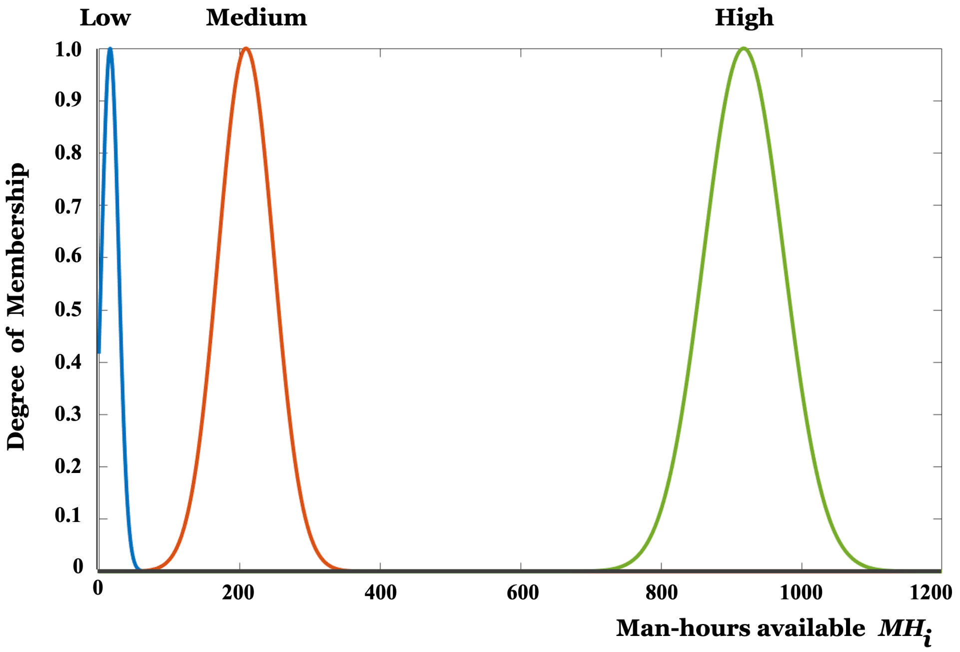

Figure 8.7. Gaussian T1MFs for man-hours available MH_i parameter

8.2 Type-2 fuzzy membership functions

The Gaussian T1MF obtained in the previous section are defined as primary MFs. Commonly, two methods are employed to add additional MF dimensionality. These are blurring either the mean or the standard deviation. The former is known as Gaussian primary MF with uncertain mean. The latter is known as Gaussian primary MF with uncertain standard deviation [181], [57]. In this thesis, Gaussian type-2 MFs are obtained by blurring the standard deviation.

For this aim, an uncertainty factor (ρ) is defined to generate the footprint of uncertainty (FOU). The upper and lower MFs in a Gaussian type-2 MF with uncertain standard deviation can be defined as [57]:

$$\overline{\mu}_{\tilde{A}}(x) = e^{\frac{-(x-c)^2}{2\sigma_2{}^2}} \tag{8.3}$$

$$\underline{\mu}_{\tilde{A}}(x) = e^{\frac{-(x-c)^2}{2\sigma_1{}^2}} \tag{8.4}$$

where c is the certain mean, the uncertain standard deviation is given by $\sigma\ [\sigma_1,\ \sigma_2]$, where $\sigma_1 = \sigma - \rho$ and $\sigma_2 = \sigma + \rho$, respectively. The upper and lower membership functions are identified by $\overline{\mu}_{\tilde{A}}(x)$ and $\underline{\mu}_{\tilde{A}}(x)$, respectively. Figure 8.8 depicts a primary Gaussian MF (see dashed line), an upper MF (see solid red line), and a lower MF (see solid green line) resulting from the effect of blurring the standard deviation such as $\sigma\ [\sigma_1,\ \sigma_2]$. In contrast to its triangular and trapezoidal counterparts, the Gaussian shape requires only three parameters for its construction. For uncertain stand deviation, the required parameters are $(c, \sigma_1,\ \sigma_2)$. Correspondingly, for uncertain mean the required parameters are $(\sigma, m_1,\ m_2)$ [181].

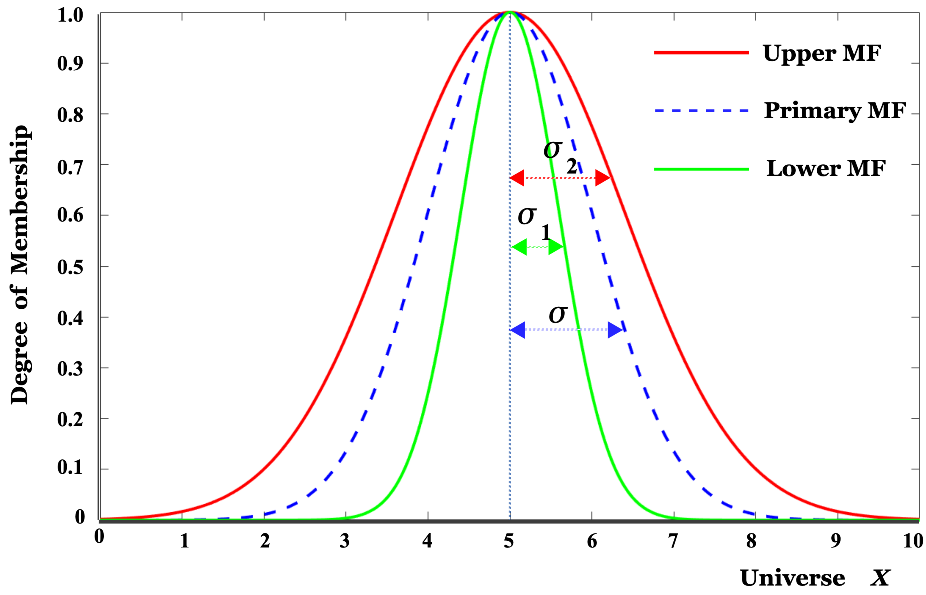

Figure 8.8. Example of Gaussian MFs for uncertain standard deviation (Source [57])

8.2.1 Demonstration of Gaussian type-2 membership functions generation

To demonstrate the construction of a Gaussian T2MF, let us retrieve from Table 8.1, the mean and standard deviation for each linguistic label referring to the number of locations visited LV_i parameter. Then, with an uncertainty factor $\rho = 2$ we obtain new values for σ_1 and σ_2 in each of the memberships for the linguistic terms.

Figure 8.9 illustrates this construction, for example, for the linguistic term $\{low\}$ the mean is found at 28.53 and the lower MF is given by $\sigma_1 = 16.81 - 2 = 14.81$. Similarly, the upper MF is defined by $\sigma_2 = 16.81 + 2 = 18.81$. For the linguistic term $\{medium\}$ the mean is at 95.39, the lower MF is given by $\sigma_1 = 5.08 - 2 = 3.08$ and the upper MF is defined by $\sigma_2 = 5.08 + 2 = 7.08$. Analogously, the linguistic term corresponding to $\{high\}$ has a mean value of 108.89, the lower MF is given by $\sigma_1 = 3.84 - 2 = 1.84$ and the upper MF is defined by $\sigma_2 = 3.84 + 2 = 5.84$. In the resulting plot the primary MFs are indicated with dashed lines, and the coloured area corresponds to the resulting FOU in each MF.

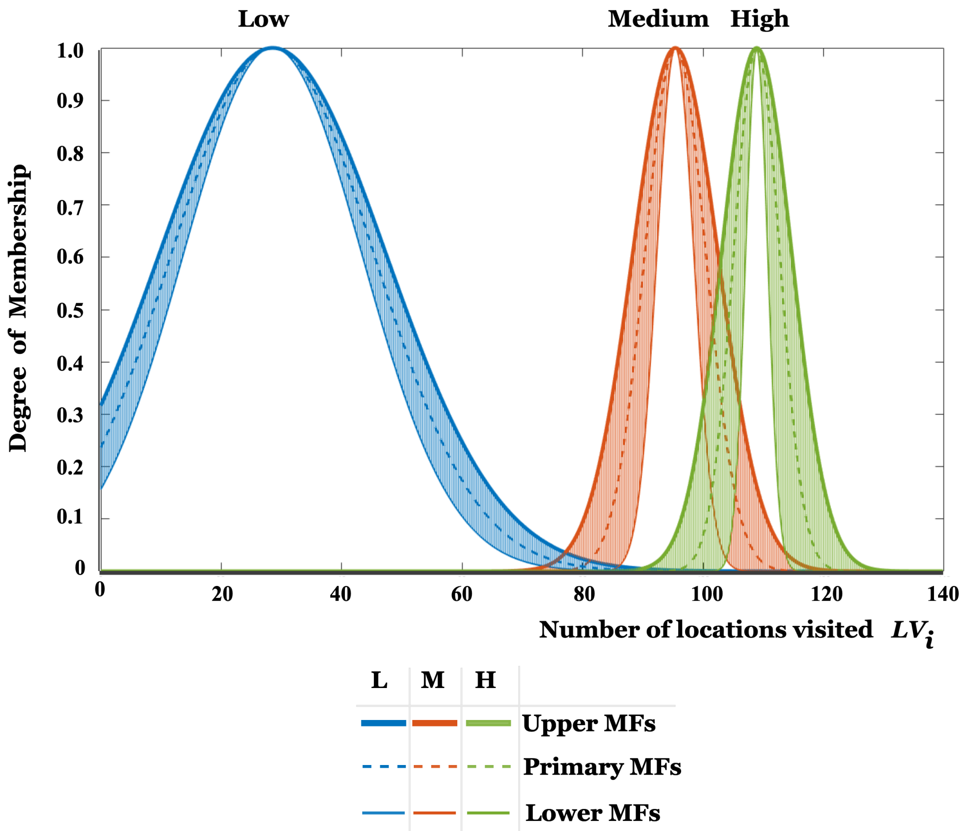

Figure 8.9. Example of Gaussian T2MFs for the number of locations visited LV_i parameter

8.3 Fuzzy rules

The methods for fuzzy rules extraction from data detailed in sections 7.2.2 and 7.3.2 are valid for this section. The only difference is that contrary to the procedure followed in Chapter 7, where the rule extraction was guided for a previous input and output identification process, in this chapter, that identification process is omitted. Consequently, the model now combines all fuzzy sets to create in the first instance a complex rule base. A major benefit of this approach is the minimisation of expert assistance to identify relevant inputs and outputs that relate to certain business targets. Hence, the need for a concise strategy to assist input and output selection.

The following section provides the foundation to carry out fuzzy correlation analysis. Successively, it details a methodology to assist systematically in the parameter selection capability of the model.

8.4 Strategy for input and output selection

Robust simulation systems require mechanisms to evaluate which inputs are relevant. In classical statistical theory, correlation helps to measure the strength of a linear relationship between two variables. Particularly, both correlation analysis and regression analysis support classical statistics [182]. However, the GDS model developed in this thesis is not modelled by classical linear concepts.

Therefore, fuzzy membership correlation analysis is employed for improving the GDS performance and target-oriented capabilities. This effort allows focusing on the input parameters that are highly related to the achievement of the desired business targets while providing sensible accuracy and concise interpretability.

8.4.1 Fuzzy correlations

Various real-world applications, such as pattern recognition and decision-making, have employed successfully fuzzy correlation measures [182]. Overall, the value of the fuzzy correlation measure ranges between [-1, 1]. Where zero indicates no linear dependence between two fuzzy sets. Similarly, one denotes perfect positive linear dependence between those fuzzy sets. Finally, negative one indicates where these two fuzzy sets are negatively correlated [182].

Fuzzy correlation measures have demonstrated notorious advantages over classical arithmetic correlations [182]. Consequently, significant research on fuzzy correlation and its applications has been carried out across various domains such as network applications [183], [184] and [185], and especially on performance predictability [186], among others.

This thesis proposes a method for fuzzy correlation analysis to assist systematically in the input/output selection, which addresses issues such as random parameter choice or the dependency of experts to guide the input/output identification. Indeed, the proposed method enhances the interpretability of the underlying rules with respect to their antecedent and consequent parts. Finally, one of the scalability criteria detailed in Section 5.5 is being enhanced by this fuzzy correlation analysis methodology. This relates to performance and simulation size. Consequently, more goals will be incorporated into the experiments.

The following subsections detail the foundations for building strategies based on fuzzy correlation analysis.

8.4.1.1 Fuzzy measurement and fuzzy simple correlation coefficient analysis

In real-world operations, crisp observations such as the number of available tasks to be completed or the number of available resources must not be considered precise. This because various factors can intervene and produce alteration on those expected crisp values. To better illustrate this idea, let us consider the following example: assume that for a certain date, the number of available tasks to be completed was expected to be a X crisp value. However, on that date, the customer cancelled for a personal related issue. Therefore, in reality, that value is not precise, and it does not reflect with certainty the real number of available tasks to be completed. Analogously, if an engineer faces some external issue such as a vehicle breakdown, the number of available resources is also unreliable. Therefore, both observations reflected some uncertainty due to external factors. Remarkably, fuzzy logic enables modelling crisp observations in an imprecise manner.

Consequently, there is a need for handling numerical measures in an approximate fashion. Notably, fuzzy correlations provide the foundations to develop such strategies. In this context, the two concepts are vital—namely, fuzzy measurements and simple correlations.

A *fuzzy measurement* can be defined as an approximate representation that reflects the inaccuracy and uncertainty inherent in real-world observations [187]. A widely accepted approach to model and interpret fuzzy measurements is the fuzzy set theory (for a sensible review of fuzzy logic see Chapter 3). Therefore, a fuzzy measurement is a fuzzy set M on a crisp universal set X that exist on the real numbers $\mathcal{R}$, defined as a set of ordered pairs in the following form [187]:

$$M = \{ (x, \ \mu_M (x)) \mid x \in \mathcal{R}, \ \mu_M (x) \in [0,1] \} \tag{8.5}$$

Therefore, if two fuzzy sets are present, then knowing the strength of their linear relationship can be useful to determine their mutual influence. Thus, *fuzzy simple correlation coefficient* formalises this relationship between two fuzzy sets [188]. Consequently, considering two fuzzy sets $A, B \subseteq F$, where F denotes a fuzzy space. The fuzzy sets A and B with membership functions μ_A and μ_B can be expressed as follows [188]:

$$A = \{(x, \ \mu_A(x)) \mid x \in X \} \tag{8.6}$$

$$B = \{(x, \ \mu_B(x)) \mid x \in X\} \tag{8.7}$$

where the membership functions are constrained in the range $[0,1]$, such as $\mu_A(x){:}\,X \rightarrow [0,1]$, and $\mu_B(x){:}\,X \rightarrow [0,1]$. Therefore, the simple correlation coefficient ρ between the fuzzy sets A and B can be computed as follows [188]:

$$\rho_{A,B} = \frac{\sigma_{A,B}}{\sigma_A \cdot \sigma_B} \tag{8.8}$$

where $\sigma_{A,B}$ denotes the covariance of fuzzy sets A and B and this can be computed as follows [188]:

$$\sigma_{A,B} = \frac{\sum_{i=1}^{n}(\mu_A(x_i) - \bar{\mu}_A)(\mu_B(x_i) - \bar{\mu}_B)}{n-1} \tag{8.9}$$

where $\bar{\mu}_A$ and $\bar{\mu}_B$ represent the average membership grades of the fuzzy sets A and B, respectively. Which can be computed as follows:

$$\bar{\mu}_A = \frac{\sum_{i=1}^{n} \mu_A(x_i)}{n} \tag{8.10}$$

$$\bar{\mu}_B = \frac{\sum_{i=1}^{n} \mu_B(x_i)}{n} \tag{8.11}$$

Consequently, the standard deviation of fuzzy sets A and B are given by the following equations:

$$\sigma_A = \sqrt{\frac{\sum_{i=1}^{n} (\mu_A(x_i) - \bar{\mu}_A)^2}{n-1}} \tag{8.12}$$

$$\sigma_B = \sqrt{\frac{\sum_{i=1}^{n} (\mu_B(x_i) - \bar{\mu}_B)^2}{n-1}} \tag{8.13}$$

A fuzzy simple correlation coefficient can have five outcomes [188]:

- When $\rho_{A,B}$ is close to 1, the fuzzy sets A and B are highly related.
- When $\rho_{A,B}$ is close to 0, the fuzzy sets A and B are barely related.
- When $\rho_{A,B} > 0$, the fuzzy sets A and B are positively related.
- When $\rho_{A,B} < 0$, the fuzzy sets A and B are negatively related.
- When $\rho_{A,B} = 0$, the fuzzy sets A and B are not related at all.

The outlined fuzzy correlation foundations are useful to analyse two fuzzy sets. Commonly, real-world problems encompass more than two fuzzy sets. Consequently, the imminent interest is to know the relationship between the two fuzzy sets if other fuzzy sets can be held constant. The following subsections introduce an approach to assist in these situations.

8.4.1.2 Fuzzy Partial Correlation Analysis

When two fuzzy sets are being evaluated, a fuzzy simple correlation analysis, as indicated in the previous section is enough. However, real-world applications demand the use of multiple-input parameters. Consequently, the analysis of two purely fuzzy sets needs to be extended. This to show the relationship between two fuzzy sets when the influence of another fuzzy set is removed from the observed fuzzy sets [189]. Without loss of generality, assume that the following relations denote the simple correlation coefficients of three fuzzy sets, namely A, B and C: $\rho_{A,B}, \rho_{B,C}$ and $\rho_{A,C}$. Then, the fuzzy partial correlation between the fuzzy sets A and B, when the effects of the fuzzy C are removed from fuzzy sets A and B, can be defined as follows [188]:

$$\rho_{A,B \cdot C} = \frac{\rho_{A,B} - \rho_{A,C} \cdot \rho_{C,B}}{\sqrt{1 - (\rho_{A,C})^2} \cdot \sqrt{1 - (\rho_{B,C})^2}} \tag{8.14}$$

From Equation (8.8) it can be generalized that $\rho_{A,B} = \rho_{B,A}$, therefore, the following expression is equivalent:

$$\rho_{B,A \cdot C} = \frac{\rho_{B,A} - \rho_{B,C} \cdot \rho_{C,A}}{\sqrt{1 - (\rho_{B,C})^2} \cdot \sqrt{1 - (\rho_{A,C})^2}} = \rho_{A,B \cdot C} \tag{8.15}$$

where the resulting fuzzy partial correlation coefficient will be different to zero as long $\rho_{A,C} \neq 0$ and $\rho_{B,C} \neq 0$. In other words, a nonzero value results from Equation (8.15) if the third fuzzy set C has a relationship with the fuzzy set A and also has a relationship with the fuzzy set B.

8.4.2 The proposed fuzzy membership correlation analysis

In principle, fuzzy rules are the result of combining all membership functions among all fuzzy sets. Therefore, the resulting rule base models all intrinsic relationships among the fuzzy attributes that characterise the available data. Consequently, a collection of fuzzy items can be described as $F = \{ f_1, f_2, .., f_m\}$ and a group of fuzzy records can be described as $X = \{ x_1, x_2, .., x_n\}$, where each fuzzy record x_i is represented as a vector with m values. Then, we can associate the membership functions and their combined rules as an implication form, such as $F_A \Rightarrow F_B$, where $F_A, F_B \subset F$ are two fuzzy items and the association $F_A \Rightarrow F_B$ holds in X with the fuzzy support that can be computed as follows [190]:

$$supp\ (\{F_A, F_B\}) = \frac{\sum_{i=1}^{n} min\left(\mu_{f_j}(x_i) \mid \mu_{f_j} \in \{F_A, F_B\}\right)}{n} \tag{8.16}$$

Correspondingly, the fuzzy confidence can be computed as follows:

$$conf\ (\{F_A \Rightarrow F_B\}) = \frac{supp\ (\{F_A, F_B\})}{supp\ (\{F_A\})} \tag{8.17}$$

Consequently, the strategy to remove irrelevant fuzzy items from the fuzzy rules and conserve only those fuzzy sets that are correlated is based on the aforementioned fuzzy correlation principles. The aim is to update the rule base with relevant rules that reflect relationships among the fuzzy sets. Therefore, the following algorithm describes this proposed strategy:

- *Step 1:* For each fuzzy item f_j, where $f \in F$ and $j = \{1,2, \dots, m\}$. Where the collection of fuzzy sets corresponds to $F = \{ f_1, f_2, .., f_m\}$ compute the fuzzy support as indicated in Equation (8.16).

- *Step 2:* Determine the minimal fuzzy support s_f as follows:

$$s_f = \sum_{i=1}^{n} min\big(supp_j(x_i)\ \big|supp_j \in \{F_A, F_B\}\big) \tag{8.18}$$

- *Step 3:* For each fuzzy support computed in step 1 that is greater than the minimal fuzzy support s_f computed in step 2, assign an element L_1:

$$L_1 = \{f_j | f_j \in F, supp\big(f_j\big) \geq s_f \} \tag{8.19}$$

- *Step 4:* For each element L_1 obtained in step 3, generate a vector V_2 with the set of combinations L_1 join with L_1 such as:

$$V_2 = \{(F_A, F_B), F_A, F_B \in L_1, F_A \neq F_B \} \tag{8.20}$$

- *Step 5:* For each pair element of V_2 obtained in step 4, compute the fuzzy support as indicated in Equation (8.16). Similarly, compute the fuzzy partial correlation coefficient $\rho_{A,B \cdot C}$ as indicated in Equation (8.14). Where, C is the fuzzy set to be removed that satisfies:

$$C = C_i \neq F_A \neq F_B \tag{8.21}$$

- *Step 6:* Determine the minimal fuzzy partial correlation coefficient as follows:

$$r_f = \sum_{i=1}^{n} min\left(\rho_{A,B \cdot C_j}(x_i) |\ \rho_{A,B \cdot C_j} \in \{F_A, F_B\}\right) \tag{8.22}$$

- *Step 7:* Generate a vector of pairs L_2 such as:

$$L_2 = \{f_j | f_j \in F, supp(f_j) \geq s_f \; ; \; r_f\} \tag{8.23}$$

- *Step 8:* Repeat from step 5 until all fuzzy sets are being evaluated and Equation (8.23) holds. Therefore, only relevant fuzzy attributes will remain in the vector of pairs V_2.
- *Step 9:* For all the elements in the resulting vector of pairs V_2 compute the fuzzy confidence as indicated in Equation (8.17) and determine the minimal fuzzy confidence as follows:

$$c_f = \sum_{i=1}^{n} min(conf_j(x_i) \, | conf_j \,) \tag{8.24}$$

- *Step 10:* If the fuzzy confidence $conf\ (\{F_A \Rightarrow F_B\})$ of a pair of fuzzy sets contained in the vector of pairs V_2 is greater or equal to the fuzzy confidence c_f obtained in Equation (8.24) then keep. Otherwise, remove from the rule and update the rule base.

8.5 Similarity evaluation

Fuzzy rule-based systems are often challenged by having in advance all the possible rules corresponding to all the possible combinations of the antecedents. As any data-driven model, the proposed GDS could face this phenomenon and be unable to find a rule that reflects the combination of the given antecedents. Therefore, misclassification will occur inevitably. This problem is commonly observed when modelling real-life systems, and it reflects the role of uncertainties related to incomplete information regarding the system inputs. Hence, a sensible data-driven model must deal with impreciseness, ambiguity, and inconsistency.

Data-driven models have employed the notion of similarity to handle this misclassification problem. Essentially, similarity identifies the relationships that characterise conceptual or perceptual entities [191]. Broadly speaking, similarity can be calculated from different angles, including mathematical, psychological, and fuzzy approaches [192].

Mathematical approaches employ distance functions to calculate the similarity between pairs of numerical data, examples of these distance functions include the Hamming [193] and the Euclidean distances [194] among others.

Psychological approaches focus on the human judgment of similarity on both theoretical and empirical grounds [195]. For this purpose, psychologists have developed parametric, nonparametric, and semiparametric categorisation models [196].

Although mathematical and psychological approaches offer solid foundations to evaluate similarity in data-driven models, they present certain shortcomings. The former often requires normalization of continuous features to effectively calculate a similarity value [197], in addition, selecting the most suited distance function for a given problem is commonly not a trivial task [198]. The latter works for binary features only, this limits similarity assessment in complex real-life scenarios.

Fuzzy approaches overcome the mentioned drawbacks by simulating the human perception of similarity. These employ fuzzy set theory to handle non-numerical descriptions. The notion of similarity in fuzzy set theory was first introduced by Professor Zadeh [199]. Initially, this defined the properties of a similarity relation between elements of a fuzzy set as reflexive, symmetric, and transitive. Similarity subsequently included measures between fuzzy sets and between elements [200]. Later, a model named Fuzzy Feature Contrast (FFC) defined similarity as an operation to assess similarity from fuzzy judgment of properties [201].

Similarity indices were improved with the appearance of the Generalised Tversky Index (GTI) [202]. GTI excels mainly in two aspects. The former at handling ambiguities, the latter at identifying whether the similarity assessment has an appropriate context or not. GTI is considered a fuzzy extension and generalisation of various similarity indices available in the literature such as the Jaccard similarity measure which is widely used in IT2 FLs [202]. The Jaccard coefficient $s^{a}_{J,IT2}$ of two fuzzy sets $\tilde{A}$ and $\tilde{B}$ represent the ratio between the intersections and the unions of their common areas, it can be defined as [203]:

$$s^{a}_{J,IT2}(\tilde{A},\tilde{B}) = \frac{(\underline{\mu}_{\tilde{A}} \cap \underline{\mu}_{\tilde{B}})_a + (\bar{\mu}_{\tilde{A}} \cap \bar{\mu}_{\tilde{B}})_a}{(\underline{\mu}_{\tilde{A}} \cup \underline{\mu}_{\tilde{B}})_a + (\bar{\mu}_{\tilde{A}} \cup \bar{\mu}_{\tilde{B}})_a} \tag{8.25}$$

As can be observed from Equation (8.25), the Jaccard coefficient requires to know in advance the upper and lower memberships of the two fuzzy sets $\tilde{A}$ and $\tilde{B}$. However, every time a misclassification occurs one of the two fuzzy sets is known. Therefore, a different similarity measure needs to be implemented to handle misclassification issues.

Therefore, misclassification cases are solved by selecting the most similar rule to provide a corresponding answer. To achieve this, the distance between two linguistic labels present in the antecedent part of the fuzzy rules is given by the following function $\mathfrak{D}(A_i^{(t)}, A_i^{(q)})$ where A is the linguistic label for the antecedent part being evaluated. To illustrate this concept, let us assume the following ordered coded: {"*low*", "*medium*", "*high*"}. Consequently, $\mathfrak{D}(low, medium) = 1$, similarly, $\mathfrak{D}(low, high) = 2$. Therefore, for each misclassified input $x^{(t)}$, compute the similarity relation with each rule R_q in a V number of fuzzy sets for the available number of inputs n as indicated as follows [204]:

$$S(x^{(t)}, R_q) = \frac{\sum_{i=1}^{n}\left(1 - \frac{\left(A_i^{(t)}, A_i^{(q)}\right)}{V-1}\right)}{n} \tag{8.26}$$

The more similar rule is given by the higher similarity distance value. Therefore, a misclassification case will be solved with the consequent class of the rule R_{q^*} by computing the similarity value for each rule $R_q, q = 1,..,M$ and finding $R_{q^*}, q^* \in \{1,..,M\}$ as follows [204]:

$$S(x^{(t)}, R_{q^*}) \geq S(x^{(t)}, R_q), \forall\, q = 1,..M \tag{8.27}$$

8.6 Experiments for the type-2 Fuzzy Logic System for GDS

The aim of this section is to provide a portfolio configuration that facilitates achieving certain business goals. The business goals studied in this section are reported in Table 8.2. These experiments were conducted in two stages: first, a data acquisition procedure was carried out following the specification outlined in Section 6.2.1, next the training and testing phases were conducted.

The resulting data set that encompasses a total of 215,091 task was split randomly in 70% training and 30% testing. The total estimated duration for this sample is 1,461,281 hours. The different levels of FOU were adjusted empirically. Performance is given by the accuracy achieved through the results, which is measured confirming the RMSE as indicated in Equation (7.40).

Table 8.2– Business objectives for the incremental GDS approach.

Goal	Business Goal Description
1	How to schedule 99% of tasks
2	How to achieve a success rate of 97% for Provision Appointments
3	How to utilise 99% of the workforce
4	How to achieve a success rate of 97% for Repair Appointments
5	How to achieve a success rate of 97% for Provision Non-Appointments
6	How to achieve a success rate of 97% for Repair Non-Appointments

The results are analysed by measuring performance among four players. These are the type-1 FLS, the initial version type-2 FLS, this enhanced version type-2 FLS and an artificial neural network. The next subsection introduces this new player and its role for benchmarking purposes.

8.6.1 Benchmarking

This benchmarking exercise focuses on evaluating the performance of the type-2 FLS by setting a comparison standard. A suitable candidate for this assessment requires to map any input and output attributes regardless of the complexity of their underlying relationship. These characteristics are found in artificial neural networks (ANNs). Hence, the use of an ANN for this comparison purpose. ANNs are known to be universal approximators, and they are used extensible in a wide range of problems.

ANNs are processing elements organised in a network structure that mimic some process found in the brain [53]. Generally, their performance seems to improve when more data is available. They are considered to be part of the black-box theory. Commonly, neural networks that implement few numbers of hidden layers are known as *shallow* neural networks. Consequently, to situate the proposed GDS approach within a reference frame, a shallow feed-forward back-propagation neural network is implemented by employing the neural network MATLAB built-in tool.

Without loss of generality, layers aggregate the elementary units known as neurons. Each neuron handles inputs and generates a single output which can be sent to other neurons. Outputs are generated by employing a transfer function. Transfer functions also, known as activation or transformation functions, are responsible for evaluating whether a neuron should be activated or not. These functions apply mathematical operations such as weighted sums and bias additions. There are multiple variants of transfer functions; these include linear and non-linear functions, among others. Non-linear functions are popular because they enable the learning capability of ANNs [74].

These experiments implement one shallow neural network for each business goal. Therefore, every network implemented is a two-layer feed-forward back-propagation shallow neural network with $I - 2X10 - O$, where the inputs are denoted by I, there are 2 hidden layers with 10 neuros each and the outputs are represented by O. The generated outputs are required to range between [0,1] with smooth gradient transition. Consequently, the transfer function employed is the sigmoid function as stated in Equation (8.28) [74].

$$\delta(x) = \frac{1}{1+ e^{-x}} \tag{8.28}$$

Since the number of expected weights is considered low, the Levenberg-Marquardt algorithm was employed for training. The network is trained until the mean squared error is below a threshold value equal to 0.010, or the number of iterations is above a threshold value equal to 2,000. Figure 8.10 depicts a generic representation of a shallow NN with 2 hidden layers. As can be observed, the outputs of each precedent layer are the inputs of the following layer. Neurons are represented by $S1, S2$ and $S3$, the biases are all a constant input 1, $f1, f2$ and $f3$ represent the activation function, and the output of the NN is denoted by y.

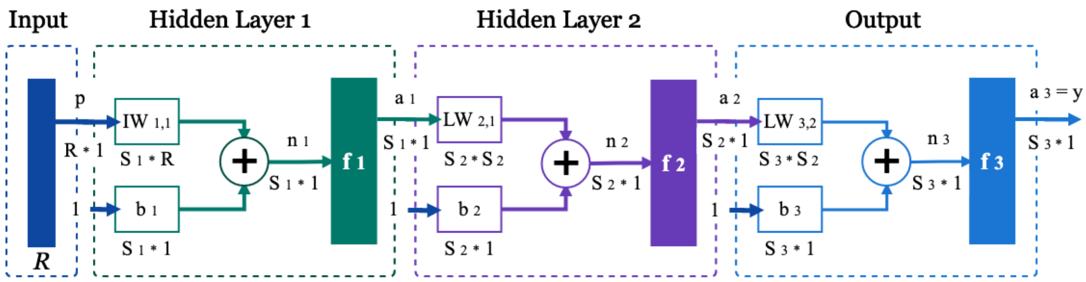

Figure 8.10. Representation of a feed-forward shallow NN (Source: [74])

8.6.2 Inputs and outputs resulting from fuzzy membership correlation analysis

Table 8.3 reports the relationship between inputs and outputs for each goal sought in these experiments. It is worth to recall that these parameters are a subset of the input/output parameters available in the model.

Table 8.3– Inputs and outputs for each business target, where I denotes input and O denotes output.

Abbreviation	Description	Goal					
		1	2	3	4	5	6
R_i	Available resources	I	I	I	I	I	I
J_i	Available jobs	I	I	I	I	I	I
WT_i	Available working time	I					
MHA_i	Man-hours available			O			
$MSRA_i$	Multi Skilled Resources Allocated		O		O		
PJS_i	Percentage Jobs scheduled	O					
PRU_i	Percentage resource utilisation			I			
PAS_i	Provision appointment scheduled	O	O				
PNS_i	Provision non- appointment scheduled					O	
$PPAS_i$	Percentage provision appointment success		I				
$PPNAS_i$	Percentage provision non- appointment scheduled					I	
$PRAS_i$	Percentage repair appointment success				I		
$PRNAS_i$	Percentage repair non- appointment scheduled						I
RAS_i	Repair appointment scheduled	O			O		
RNS_i	Repair non- appointment scheduled						O
$SSRA_i$	Single skilled resources allocated			O			

The fuzzy membership correlation analysis is carried out as detailed in Section 8.4.2. The aim is to update the rule base with relevant rules that reflect relationships among the fuzzy sets. This step is computationally expensive because all the input/output vectors are combined, as explained in Section 8.3. Additionally, the data volume in these experiments increased five times with respect to the data volume employed in the experimentations carried out in Section 7.4. However, the benefit of adding this capability to the model is a differentiator worth the cost.

The following subsection will provide all the required parameters to build the corresponding fuzzy membership functions.

8.6.3 Type-1 and type-2 MFs

These experiments implement Gaussian membership functions with uncertain standard deviation. To generate the T1MFs only the mean and the standard deviation are required. These values are available from the fuzzy clustering carried out in Section 8.1. The T2MFs are obtained by blurring the standard deviation. This is performed empirically for all the available fuzzy sets.

Table 8.4 reports the required values for the Gaussian T1MFs and T2MFs. Where the column F reports the abbreviated input/output parameters. Each linguistic label reports their mean c, their standard deviation σ employed to generate the primary MF, their standard deviation σ_2 used to obtain the upper MF, and their standard deviation σ_1 used to produce the lower MF.

Table 8.4– Values to demonstrate Gaussian T1 and T2 MFs generation.

F	Low			Medium			High		
	c	σ	$[\sigma_1,\sigma_2]$	c	σ	$[\sigma_1,\sigma_2]$	c	σ	$[\sigma_1,\sigma_2]$
R_i	25.90	9.77	[8.27, 11.27]	106.76	2.98	[1.48, 4.48]	118.80	4.40	[2.9, 5.9]
J_i	57.49	28.53	[27.03, 30.03]	366.64	31.02	[29.52, 32.52]	486.67	51.37	[49.87, 52.87]
TTH_i	20.23	13.17	[11.67, 14.67]	106.91	13.68	[12.18, 15.18]	150.74	13.25	[11.75, 14.75]
TJH_i	64.80	39.78	[38.28, 41.28]	409.37	33.40	[31.9, 34.9]	521.09	27.78	[26.28, 29.28]
TPA_i	4.36	7.62	[6.12, 9.12]	100.76	17.83	[16.33, 19.33]	156.05	23.30	[21.8, 24.8]
MHA_i	16.10	12.16	[10.66, 13.66]	209.40	39.58	[38.08, 41.08]	917.68	56.90	[55.4, 58.4]
MH_i	1.01	85.80	[84.3, 87.3]	220.80	27.01	[25.51, 28.51]	908.87	38.39	[36.89, 39.89]
LV_i	28.53	16.81	[15.31, 18.31]	95.39	5.08	[3.58, 6.58]	108.89	3.84	[2.34, 5.34]
RJ_i	2.06	1.49	[0.01, 2.99]	24.67	4.78	[3.28, 6.28]	108.30	6.77	[5.27, 8.27]
ST_i	49.99	30.46	[28.96, 31.96]	290.59	34.32	[32.82, 35.82]	387.70	36.04	[34.54, 37.54]
PA_i	3.32	16.16	[14.66, 17.66]	93.08	16.16	[14.66, 17.66]	134.88	16.94	[15.44, 18.44]
PNA_i	2.67	7.70	[6.2, 9.2]	44.47	11.44	[9.94, 12.94]	104.58	15.54	[14.04, 17.04]
PAF_i	1	1.70	[0.2, 3.2]	13.63	4.55	[3.05, 6.05]	38.13	10.89	[9.39, 12.39]
$PNAF_i$	1	1.70	[0.2, 3.2]	13.63	4.55	[3.05, 6.05]	38.13	10.89	[9.39, 12.39]
RA_i	25.36	14.28	[12.78, 15.78]	128.19	10.35	[8.85, 11.85]	162.28	9.27	[7.77, 10.77]
RNA_i	3.62	12.06	[10.56, 13.56]	61.41	13.18	[11.68, 14.68]	102.20	14.59	[13.09, 16.09]
WHA_i	9.05	36.74	[35.24, 38.24]	76.34	68.34	[66.84, 69.84]	541.40	1.54	[0.04, 3.04]

For brevity, selected Gaussian T2MFs for the abovementioned input/output vectors are depicted as follows:

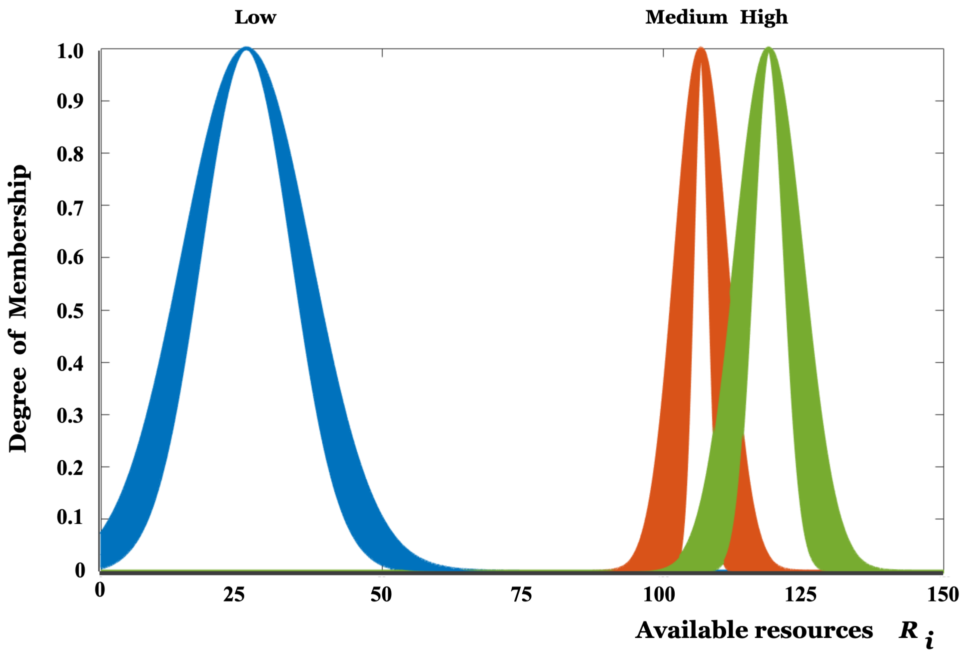

Figure 8.11. Gaussian T2MFs for available resources R_i parameter

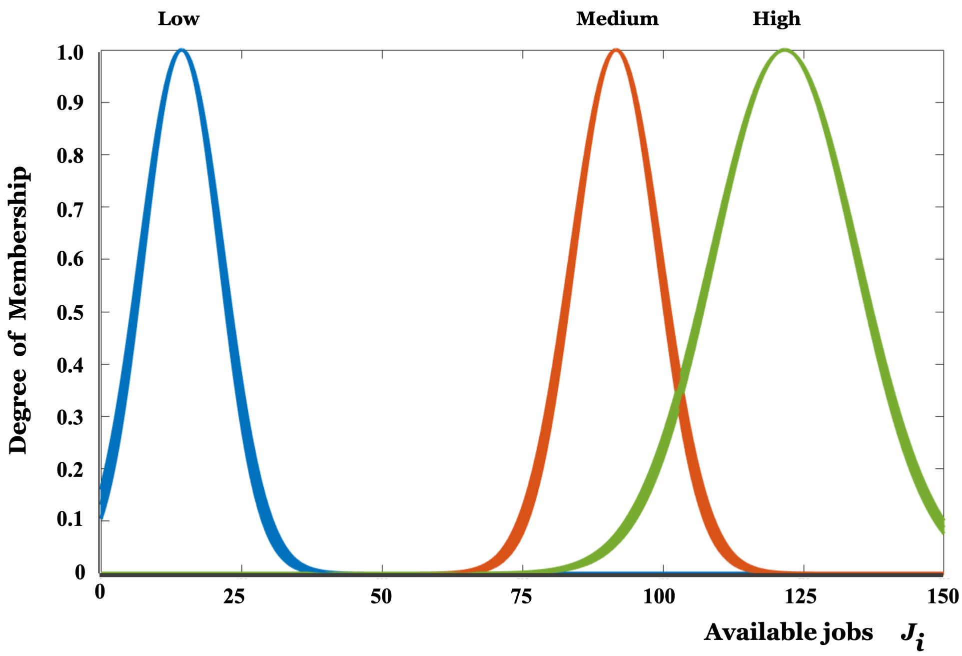

Figure 8.12. Gaussian T2MFs for available jobs J_i parameter

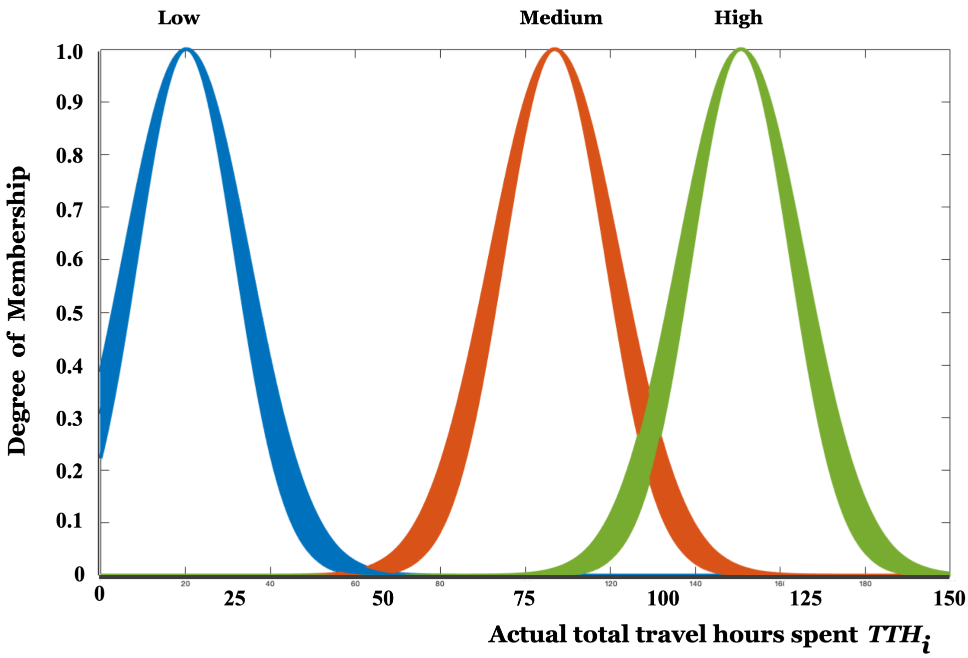

Figure 8.13. Gaussian T2MFs for actual total travel hours spent TTH_i parameter

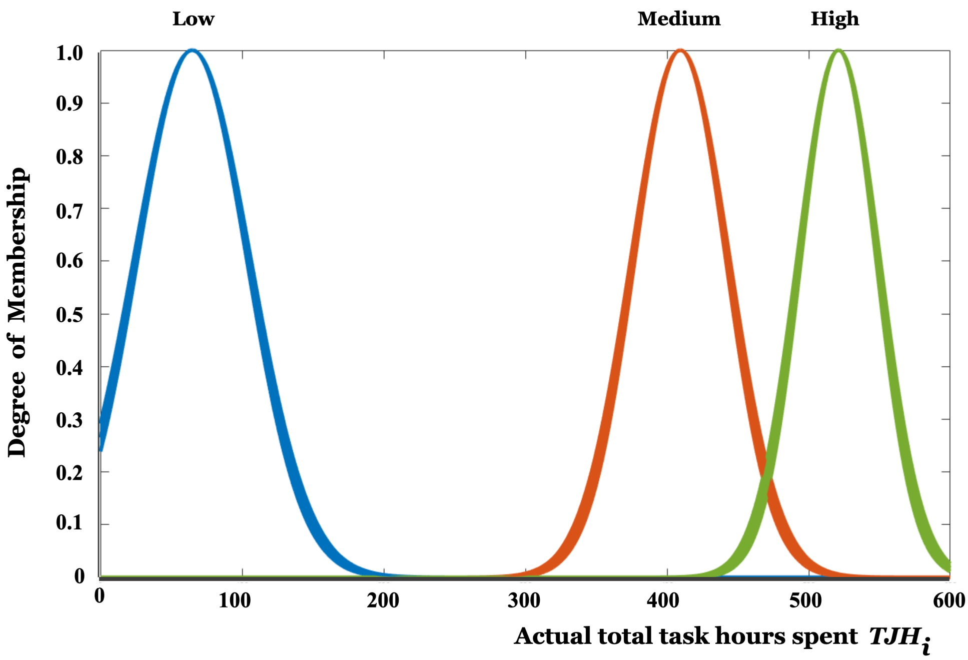

Figure 8.14. Gaussian T2MFs for Actual total task hours spent TJH_i parameter

8.6.4 Fuzzy rules for each business goal

Each goal has its own relevant parameters. Therefore, the model creates a new knowledge base with the corresponding inputs/outputs for each business goal. Table 8.5 reports the rule base for Goal 1 with the abbreviated antecedents and consequents as previously detailed in Table 8.3.

Table 8.5–Rule base for Goal 1, with a total size of 27 rules.

Rule Index	IF Antecedents			THEN Consequents		
	R_i	J_i	WT_i	PJS_i	PAS_i	RAS_i
1	Low	Low	Low	Low	Low	Low
2	Low	Low	Medium	Medium	Low	Low
3	Low	Low	High	High	Low	Low
4	Low	Medium	Low	Low	Medium	Low
5	Low	Medium	Medium	Medium	Medium	Low
6	Low	Medium	High	High	Medium	Low
7	Low	High	Low	Low	High	Low
8	Low	High	Medium	Medium	High	Low
9	Low	High	High	High	High	Low
10	Medium	Low	Low	Low	Low	Medium
11	Medium	Low	Medium	Medium	Low	Medium
12	Medium	Low	High	High	Low	Medium
13	Medium	Medium	Low	Low	Medium	Medium
14	Medium	Medium	Medium	Medium	Medium	Medium
15	Medium	Medium	High	High	Medium	Medium
16	Medium	High	Low	Low	High	Medium
17	Medium	High	Medium	Medium	High	Medium
18	Medium	High	High	High	High	Medium
19	High	Low	Low	Low	Low	High
20	High	Low	Medium	Medium	Low	High
21	High	Low	High	High	Low	High
22	High	Medium	Low	Low	Medium	High
23	High	Medium	Medium	Medium	Medium	High
24	High	Medium	High	High	Medium	High
25	High	High	Low	Low	High	High
26	High	High	Medium	Medium	High	High
27	High	High	High	High	High	High

For brevity, a subset of the rule base for Goal 2 is reported in Table 8.6. Similarly, a subset of the rule base for Goal 3 is reported in Table 8.7.

Table 8.6– Extract of rule base for Goal 2, from a total size of 27 rules.

Rule Index	IF Antecedents			THEN Consequents	
	R_i	J_i	$PPAS_i$	$MSRA_i$	PAS_i
1	Low	Low	Low	Low	Low
3	Low	Low	High	High	Low
5	Low	Medium	Medium	Medium	Medium
7	Low	High	Low	Low	High
9	Low	High	High	High	High
11	Medium	Low	Medium	Medium	Low
15	Medium	Medium	High	High	Medium
17	Medium	High	Medium	Medium	High
19	High	Low	Low	Low	Low
21	High	Low	High	High	Low
23	High	Medium	Medium	Medium	Medium
25	High	High	Low	Low	High
27	High	High	High	High	High

Table 8.7– Extract of rule base for Goal 3, from a total size of 27 rules.

Rule Index	IF Antecedents			THEN Consequents	
	R_i	J_i	PRU_i	MHA_i	$SSRA_i$
3	Low	Low	High	High	Low
5	Low	Medium	Medium	Medium	Medium
7	Low	High	Low	Low	High
9	Low	High	High	High	High
11	Medium	Low	Medium	Medium	Low
15	Medium	Medium	High	High	Medium
17	Medium	High	Medium	Medium	High
19	High	Low	Low	Low	Low
21	High	Low	High	High	Low
23	High	Medium	Medium	Medium	Medium
25	High	High	Low	Low	High
27	High	High	High	High	High

Table 8.8 reports the rule base for Goal 4 with the abbreviated antecedents and consequents as previously detailed in Table 8.3.

Table 8.8–Rule base for Goal 4, with a total size of 27 rules.

Rule Index	IF Antecedents			THEN Consequents	
	R_i	J_i	$PRAS_i$	$MSRA_i$	RAS_i
1	Low	Low	Low	Low	Low
2	Low	Low	Medium	Medium	Medium
3	Low	Low	High	High	High
4	Low	Medium	Low	Low	Low
5	Low	Medium	Medium	Medium	Medium
6	Low	Medium	High	High	High
7	Low	High	Low	Low	Low
8	Low	High	Medium	Medium	Medium
9	Low	High	High	High	High
10	Medium	Low	Low	Low	Low
11	Medium	Low	Medium	Medium	Medium
12	Medium	Low	High	High	High
13	Medium	Medium	Low	Low	Low
14	Medium	Medium	Medium	Medium	Medium
15	Medium	Medium	High	High	High
16	Medium	High	Low	Low	Low
17	Medium	High	Medium	Medium	Medium
18	Medium	High	High	High	High
19	High	Low	Low	Low	Low
20	High	Low	Medium	Medium	Medium
21	High	Low	High	High	High
22	High	Medium	Low	Low	Low
23	High	Medium	Medium	Medium	Medium
24	High	Medium	High	High	High
25	High	High	Low	Low	Low
26	High	High	Medium	Medium	Medium
27	High	High	High	High	High

Similarly, rules for Goals 5 and 6 are depicted in Table 8.9 and Table 8.10, respectively.

Table 8.9– Extract of rule base for Goal 5, from a total size of 27 rules.

Rule Index	IF Antecedents			THEN Consequents
	R_i	J_i	$PPAS_i$	$MSRA_i$
1	Low	Low	Low	Low
3	Low	Low	High	High
5	Low	Medium	Medium	Medium
7	Low	High	Low	Low
9	Low	High	High	High
11	Medium	Low	Medium	Medium
13	Medium	Medium	Low	Low
15	Medium	Medium	High	High
17	Medium	High	Medium	Medium
19	High	Low	Low	Low
21	High	Low	High	High
23	High	Medium	Medium	Medium
25	High	High	Low	Low
27	High	High	High	High

Table 8.10– Extract of rule base for Goal 6, from a total size of 27 rules.

Rule Index	IF Antecedents			THEN Consequents
	R_i	J_i	$PPAS_i$	$MSRA_i$
1	Low	Low	Low	Low
2	Low	Low	Medium	Medium
4	Low	Medium	Low	Low
6	Low	Medium	High	High
8	Low	High	Medium	Medium
10	Medium	Low	Low	Low
12	Medium	Low	High	High
14	Medium	Medium	Medium	Medium
16	Medium	High	Low	Low
18	Medium	High	High	High
20	High	Low	Medium	Medium
22	High	Medium	Low	Low
24	High	Medium	High	High
26	High	High	Medium	Medium

8.6.5 Results

The agile methodology employed in the development of this thesis aims to strengthen incrementally the proposed GDS model. Therefore, some of the shortcomings identified in previous versions are being addressed. To identify each FLS, let us refer to the systems developed in Chapter 7 as T1 FLS and T2 FLS initial versions. For the system developed in this chapter let us refer to it as T2 FLS Enhanced. Consequently, this section presents the results from various angles. Initially, these experiments employed five times more data and included two more goals. Figure 8.15 illustrates the differences in this area.

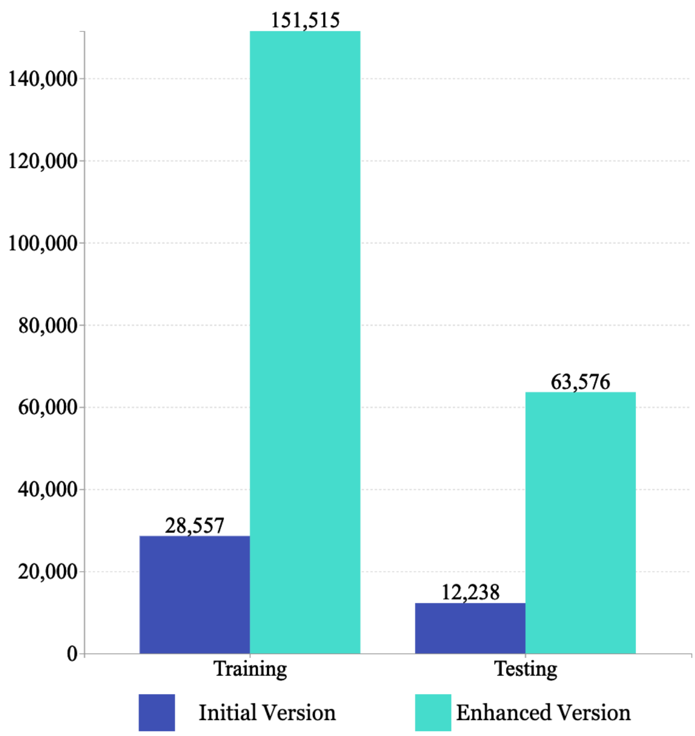

Figure 8.15. Data volume processed in initial and enhanced version

Higher data volume enables a sensible evaluation in process time. Each of the learning and testing phases for every goal encompassed 1,000 evaluation cycles. The employed computing equipment is a virtual machine (VM) with a

64-bit processor at 1.7 GHz quad-core and a maximum of 8 GB total available random-access memory (RAM). Figure 8.16 depicts the maximum distribution of time in milliseconds for the training phase. On average, the training clocked time was 2 minutes with 15 seconds in the initial version, and 7 minutes with 10 seconds in the enhanced version. This increment is due to the additional fuzzy correlation analysis feature implemented to address the input/output selection.

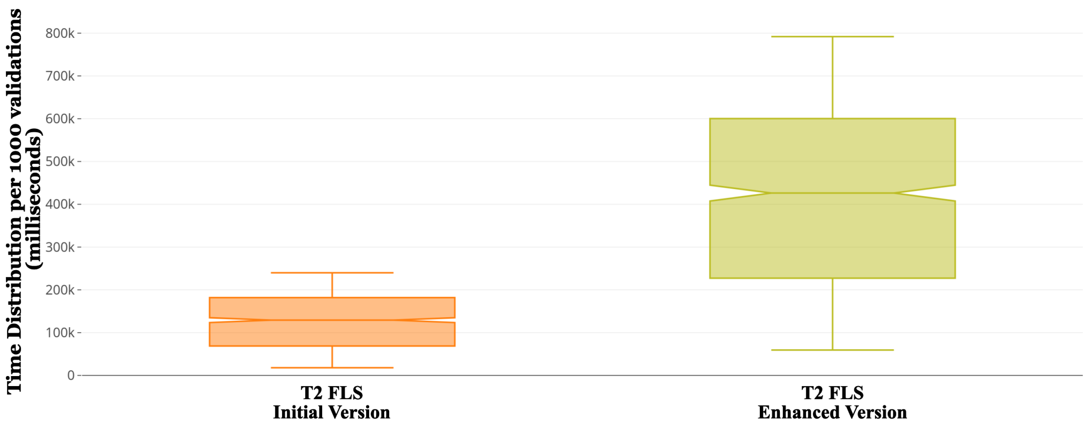

Figure 8.16. Maximum training time for initial version versus enhanced version

The fuzzy correlation analysis is computational expensive because it analyses all the fuzzy rules and keeps only those where their parameters are correlated. However, the increased cost reflects a more concise rule base. As a result, we observe less rules for each business target being sought.

It is noteworthy to point out that the parameters found by the fuzzy correlation analysis capability were in some cases different to those used in the initial version. This demonstrates that the assumptions of relevance made by experts could be different from the correlations inherent in the data. Figure

8.17 reports the total number of rules for each goal in both the initial and the enhanced versions.

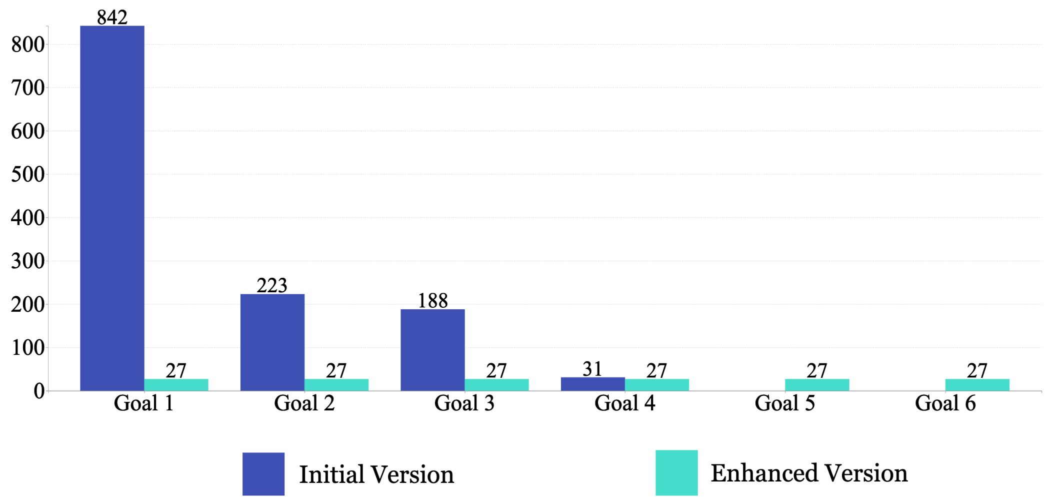

Figure 8.17. The number of fuzzy rules per business goal

As indicated in Equation (7.40), the RMSE is employed to evaluate the obtained results. Table 8.11 and Table 8.12 report the performance for training and testing, respectively.

Table 8.11– RMSE in training comparison between type-1, IT2FL (initial versions), T2 FLS (enhanced version), and ANN for all goals.

Goal	Training			
	T1 FLS (Initial Version)	T2 FLS (Initial Version)	T2 FLS (Enhanced Version)	ANN
1	0.8522452	0.6746846	0.5968733	0.3405876
2	0.5730032	0.2959931	0.2849943	0.2370167
3	0.7277007	0.5222968	0.4111857	0.2911455
4	0.3524441	0.2802045	0.1601039	0.1502808
5	0.9945181	0.9700144	0.9309289	0.5857034
6	0.9370781	0.9795844	0.9638549	0.6535476
Average	**0.739498233**	**0.620462967**	**0.557990167**	**0.376380267**

For training, Table 8.11 reports that better performance on average is obtained by the ANN. The shallow ANN outperforms its counterpart T1 FLS, T2 FLS (initial versions), and T2 FLS (enhanced version) by 49%, 39% and 32%, respectively. With respect to the enhanced T2 FLS, it can be observed that it outperforms its previous version by 10% in the training phase.

For testing, Table 8.12 reports that better performance on average is obtained by the ANN. The shallow ANN outperforms its counterpart T1 FLS, T2 FLS (initial version), and T2 FLS (Enhanced) by 50%, 41% and 40%, respectively. With respect to the enhanced T2 FLS, it can be observed that it outperforms its previous version by only 1% in the training phase.

Table 8.12– RMSE in the testing comparison between type-1, IT2FL (initial version), IT2FLS (enhanced version), and ANN for all streams.

Goal	Testing			
	Type-1 (Initial Version)	**IT2FLS (Initial Verion)**	**IT2FLS (Enhanced Version)**	**ANN**
1	0.7928875	0.6520265	0.6327269	0.3090516
2	0.5715524	0.2952001	0.2962385	0.2324312
3	0.6043349	0.4430870	0.4329598	0.2347248
4	0.3183252	0.2765011	0.25783219	0.0961514
5	0.9597750	0.9273803	0.91988963	0.5586890
6	0.9114777	0.8987632	0.89775813	0.6256429
Average	**0.693058783**	**0.5821597**	**0.572900858**	**0.342781817**

8.7 Benefits of the enhanced type-2 FLS for GDS

The agile modelling methodology is practical and allows incremental improvements. At this stage, robust capabilities toward an end-to-end framework for GDS has been incorporated. In practice, the benefits of the proposed approach for the developed experiments can be listed as follows:

1) Consistent portfolio configuration. The achieved results outperformed the initial versions developed in the previous chapter. The benefit of smaller rule bases and reduced number of antecedents and consequents did not compromise the quality of the results.
2) Scalability. This in two main aspects, the former related to higher data volume, the latter related to the increased number of business targets. Data volume increased five times, and the new two business targets were studied. This demonstrates the scalability criteria defined in Section 5.5.
3) Input and output correlations. An approach for analysing correlations that goes beyond classical linear concepts was detailed. This aligns with real-world problems, where linearity is rarely present. The benefit of this strategy allows for identifying relationships among fuzzy sets.
4) Enhanced model interpretability. A major benefit toward explainable AI models was observed with the reduction of the number of rules.

8.8 Discussion

This chapter has showcased the use of fuzzy clustering via the FCM algorithm and demonstrated the design of Gaussian T1 MFs by providing the values required for their construction. Successively, this chapter provided the principles to generate Gaussian T2 MFs by blurring the standard deviation. Sequentially, this chapter reviewed the fuzzy rules generation, and it presented a new strategy for input and output selection based on fuzzy correlation analysis. Next, this chapter presented a methodology for similarity evaluation, which enables addressing misclassification issues. Successively, this chapter developed the experiments for six business goals, where it introduced a new benchmarking element. Subsequently, this chapter reported the inputs and outputs resulting from the aforementioned fuzzy correlation analysis. Next, this chapter provided detailed values for the parameters needed to generate the corresponding Gaussian T1 and T2 MFs. These parameters were followed by the presentation of selected plots that illustrated this MFs generation. Subsequently, this chapter presented a summary of the rules involved in each business goal being sought. Successively, this chapter reported the results and presented a brief overview of the benefits of the achieved type-2 FLS enhanced version for GDS.

Each section of this chapter has devoted to providing a detailed insight into the incremental methodology to strengthen the fuzzy logic solution for GDS, with a particular focus on modelling uncertainty more effectively. In summary, fuzzy clustering allows associating each data observation to all possible valid clusters within a membership value. Therefore, this technique addresses one shortcoming reported in the initial version, developed in the previous chapter. This is the use of equally spaced membership functions. With the use of the FCM algorithm and trapezoidal and triangular MFs, the creation of Gaussian T1 and T2 MFs was easy to achieve. Trapezoidal, triangular and Gaussian shapes bring benefits to modelling. It was demonstrated that Gaussian is simple in design, and they are always continuous, while trapezoidal and triangular MFs are easier to analyse.

This chapter also demonstrated a method for fuzzy correlation analysis to assist the input and output selection systematically. This fuzzy correlation analysis methodology addresses issues such as random parameter choice or experts' dependency to guide the input and output identification. Indeed, the results reported that the proposed method enhances the interpretability of the underlying rules concerning their antecedent and consequent parts. Moreover, robust simulation systems require mechanisms to address misclassification problems. In this context, this chapter presented a strategy for similarity evaluation.

A shallow neural network served as a benchmark to measure the performance of the enhanced type-2 FLS. However, it also demonstrated that explainability is a limited feature of this black-box approaches. This increased the need for explainable, transparent and interpretable models that address regulated industries focusing on operational performance.

Each goal presented its results. The RMSE was used as a metric for performance. Overall, concerning the enhanced T2 FLS, it was reported that it outperforms the initial version by 10% in the training phase. This stage's main benefits include consistent portfolio configuration; scalability in two aspects, these are higher data volume and increased number of business targets; an approach for analysing correlations that go beyond classical linear concepts; and reduction of linguistic terms that enhance model interpretability.

Overall, the work presented in this chapter has increased robustness to the GDS model. The incremental approach has facilitated adding new capabilities and addressing identified issues. However, there is still a key feature to be reviewed, modelled and implemented. This is the incorporation of an optimisation technique to address the aforementioned issue of empirical FOU adjustments. In addition, the optimisation of the rule base is a constant aim in rule-based systems and the optimal number of antecedents and consequents as well. The following chapter will introduce an optimisation approach and will formalise the framework for the GDS problem.

Chapter 9 - The Big Bang-Big Crunch Based Type-2 Fuzzy Logic Framework for Goal-Driven Simulation

This thesis has incrementally developed each component of a fuzzy logic framework for GDS in the field service domain; this is depicted in Figure 9.1. The proposed framework enables structured end-to-end simulation capabilities of "how-to?" scenario analysis for the field service delivery domain.

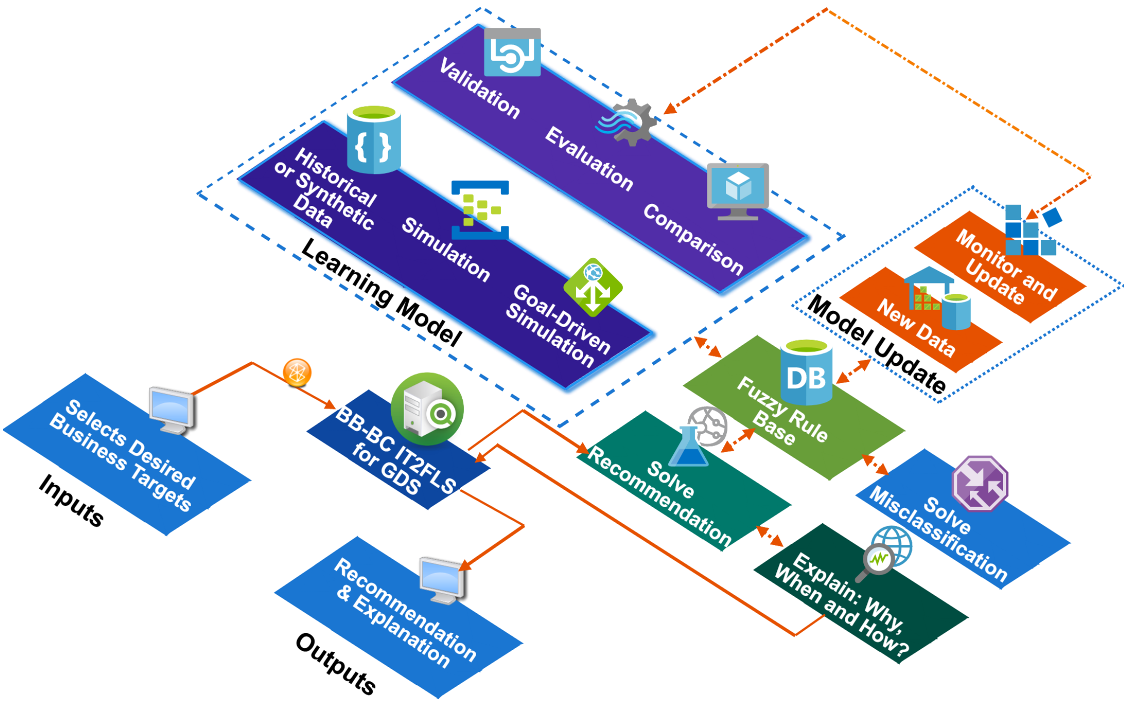

Figure 9.1. The proposed BB-BC type-2 fuzzy logic framework for GDS

This chapter formalises the proposed framework by first, enhancing the versions presented in Chapter 8, next, by outlining the main modules of the framework and presenting a set of large-scale experiments and their results. A new player is incorporated to evaluate the obtained results based on neural networks. Overall, the BB-BC T2FLS generated concise results for eight different geographical territories within the UK. The artificial neural network reported the best performance. However, because of the black-box nature of ANNs, the degree of interpretability is a known issue.

The following subsection will introduce the technique to optimise the type-2 FLS based on the big bang-big crunch. Hence, the BB-BC acronym.

9.1 The BB-BC as an optimiser

The proposed model is optimised by encompassing three aspects; these are: minimise the number of rules, optimise the footprint of uncertainty and reduce the number of antecedents for each rule in the resulting rule base. Therefore, the big bang-big crunch (BB-BC) algorithm is employed for this purpose.

The BB-BC algorithm is based on the evolution of the universe. Essentially, the BB-BC is conformed of two phases: The Big Bang phase and the Big Crunch phase. The former generates random points; the latter compact those points to a single representative point. The steps for this optimisation algorithm can be enumerated as follows [205]:

- *Step 1:* Similarly, to other search algorithms based on evolution, the initial Big Bang population is randomly generated by considering the whole research space.
- *Step 2:* The successive Big Bang phases are randomly distributed by the centre of mass that corresponds to the best-fit individual in a similar approach. Here, the cost function values of all candidates are computed.
- *Step 3:* Once completed the Big Bang phase, the Big Crunch takes place. Here, a contraction procedure is carried out to conform to a centre of mass, in the form of:

$$\vec{x}^c = \frac{\sum_{i=1}^{N} \frac{1}{f^i} \vec{x}^i}{\sum_{i=1}^{N} \frac{1}{f^i}} \quad (9.1)$$

where the position of the centre of mass is denoted by $\vec{x}^c$, the position of the candidate is given by $\vec{x}^i$, the cost function value of the ith candidate is expressed by f^i and N is the population size.

- *Step 4:* Subsequently, new candidates are calculated around the centre of mass. For this, as the iterations elapse the value of a normal distributed random number is added or subtracted, in the form of:

$$\vec{x}^{new} = \vec{x}^c + \frac{\Upsilon\rho(x_{max} - x_{min})}{k} \quad (9.2)$$

where, $\vec{x}^c$ is the centre of mass, Υ represents the normal random number, ρ denotes the parameter limiting the search space, x_{max} and x_{min} are upper and lower limits respectively, and k is the iteration step.

- *Step 5:* If the stopping criteria have not been met, then iterate from step 2. Common stopping criteria methods include reaching the maximum number of iterations, an error values that results lower than a given threshold or elapsed optimisation time [206].

The BB-BC has been implemented successfully in data clustering [207], in type-2 fuzzy PID cascade controller strategies [208], in type-2 fuzzy logic systems for machine vision [209] and in type-2 fuzzy logic based human behaviour recognition systems [210], among others.

This thesis uses the BB-BC algorithm to optimise three important aspects of a robust framework. First, minimise the number of rules contained in the rule base. Second, minimise the number of antecedents a rule level. Third, optimise the footprint of uncertainty across all fuzzy sets. The next subsection outlines the strategy for the proposed method.

9.1.1 Optimisation strategy based on the BB-BC algorithm

The proposed optimisation strategy is based on the aforementioned BB-BC method with some minor tweaks. In any successful GA implementation, the defining of the genotype is essential [53]. Therefore, encoding is a common practice when implementing optimisation solutions based on search spaces. Figure 9.2 shows a generalisation encoding example for a fuzzy rule defined by Equation (3.17). Where, $l = \{1, 2, \ldots, R\}$, R is the total number of rules and l is the rule index, x_i are the inputs, $\tilde{A}_i^l$ are the antecedents sets, i is the antecedent index $i = \{1, 2, \ldots, n\}$, and n is the total of antecedents. The output is denoted by y and $\tilde{B}^l$ are the consequent sets. The total of these rules conforms the rule base.

$$\boxed{\tilde{A}_1^1}\boxed{\cdots}\boxed{\tilde{A}_{\mathrm{n}}^1}\boxed{\tilde{B}_1^1}\boxed{\cdots}\boxed{\tilde{B}_{\mathrm{n}}^1}\boxed{\cdots}\boxed{\tilde{A}_1^l}\boxed{\cdots}\boxed{\tilde{A}_{\mathrm{n}}^l}\boxed{\tilde{B}_1^l}\boxed{\cdots}\boxed{\tilde{B}_{\mathrm{n}}^l}$$

Figure 9.2. A generalised example of encoding for a fuzzy rule

Encoding is fundamental for this proposal to work. Therefore, it is the first step of the pseudocode for the BB-BC algorithm reported in Table 9.1.

Table 9.1– Pseudocode for the BB-BC algorithm.

Pseudocode:	**Big Bang-Big Crunch Algorithm**
Input:	Fitness function, exploration factor
Output:	Optimised outcome
1:	Encoding
2:	*Initialisation*:
3:	*starting_point* = Generate a starting point based on a population randomly generated by considering the whole research space.
4:	*exploration_factor* = exploration factor
5:	*dimesnion* = Dimension of the solution.
6:	**Repeat**
7:	*Big Bang Phase:*
▶	Create mass around starting point
8:	**for** i = 1 to exploration_factor **do**
9:	**for** j = 1 to dimension **do**
10:	*mass*[i, j] = generate a candidate based on Equation (9.2)
11:	**end for**
12:	**end for**
13:	*Big Cruch Phase:*
14:	*centre_of_mass* = compute the centre of mass per Equation (9.1)
15:	*starting_point* = *centre_of_mass*
▶	update
16:	**until** max number of iteractions or convergence

Figure 9.3 depicts a generalised workflow for the optimisation strategy tailored to process any encoded genotype. The flexibility of the BB-BC itself allows using any stopping criteria or any cost function.

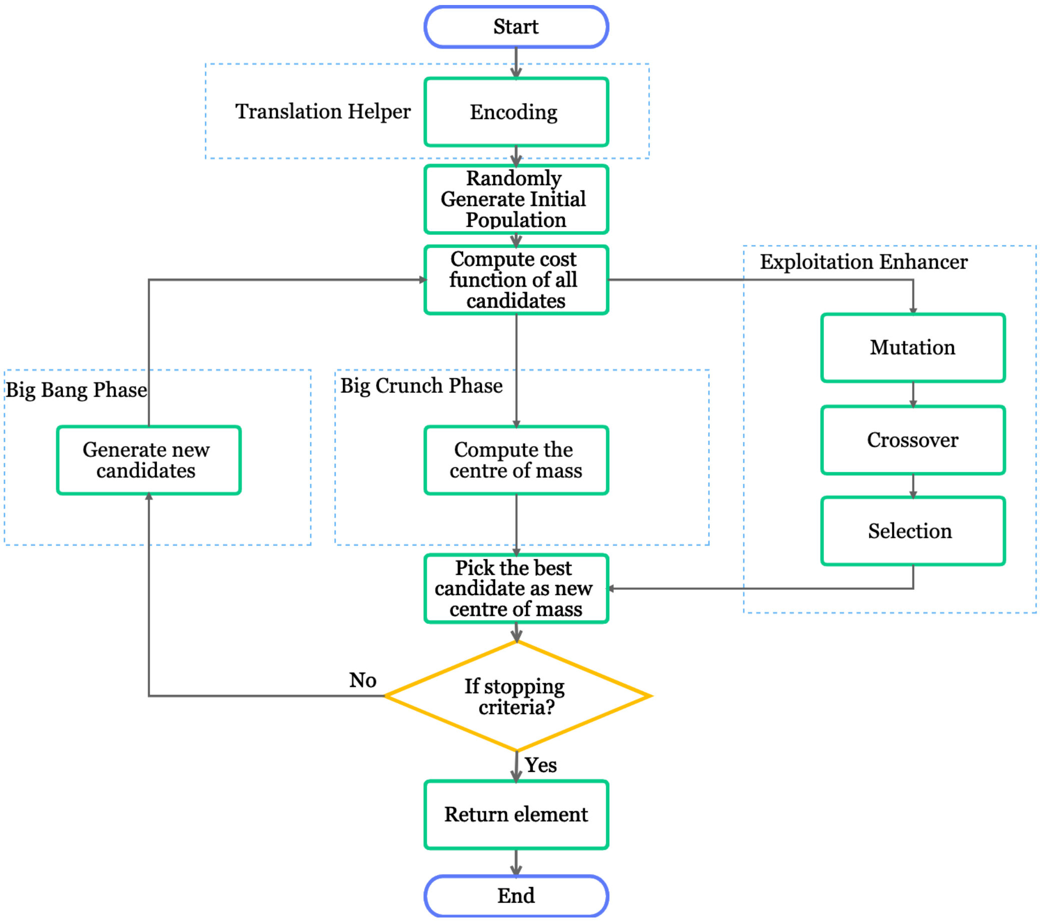

Figure 9.3. The proposed BB-BC based optimisation strategy

Figure 9.4. illustrates the encoding for a type-2 MF with three linguistic labels. Where, the fuzzy sets {*low*, *medium*, *high*} are represented by the sub-indexes *l*, *m* and *h*, respectively. The total number of inputs is given by *j*={*1,2,..,N*}. The total number of outputs is given by *k*={*1,2,..,M*}. For each input, the parameter α represents the uncertainty factor. Similarly, the parameter ϖ represents the uncertainty factor for each output.

$$\boxed{\alpha_l^1}\boxed{\alpha_m^1}\boxed{\alpha_h^1}\boxed{\cdots}\boxed{\alpha_l^j}\boxed{\alpha_m^j}\boxed{\alpha_h^j}\boxed{\varpi_l^1}\boxed{\varpi_m^1}\boxed{\varpi_h^1}\boxed{\cdots}\boxed{\varpi_l^k}\boxed{\varpi_m^k}\boxed{\varpi_h^k}$$

Figure 9.4. A generalised example of encoding for a type-2 MF

9.2 Interactive visualisation as a tool for depicting decision-making

The use of fuzzy logic for modelling facilitated communication with expert users and enabled non-expert users to follow the construction and to participate in the modelling. The use of optimisers such as the BB-BC algorithm is seen as a utility tool by the stakeholders, planners and other personnel involve in this design.

The focus has been to provide explanation, transparency and interpretation of the underlying modelling and algorithms implemented. Important factors, such as travel cost and quality of service, have been incorporated to ensure operational sustainability. Data protection regulations have been followed, and interactive visual analytics have been employed to provide transparency and facilitate consensus among all the involved parties.

This section introduces a visualisation tool for depicting the recommendations generated by the system. This work identified four elements that act as the foundation for an effective depicting process. These include a goal selector, a recommendation output, a recommendation panel and a supporting view. These elements are not exhaustive; however, they enable the minimum cognitive insight into why the system is providing a certain set of outputs.

Without loss of generality, the solution provides an overall flow of how the recommendation for GDS was conducted. Therefore, users can select a business target and obtain the system's recommendation. Users can modify the available settings directly in the simulator without the need for mastering any other knowledge. Figure 9.5 depicts the goal selector panel (see A) and the recommendation panel (see B).

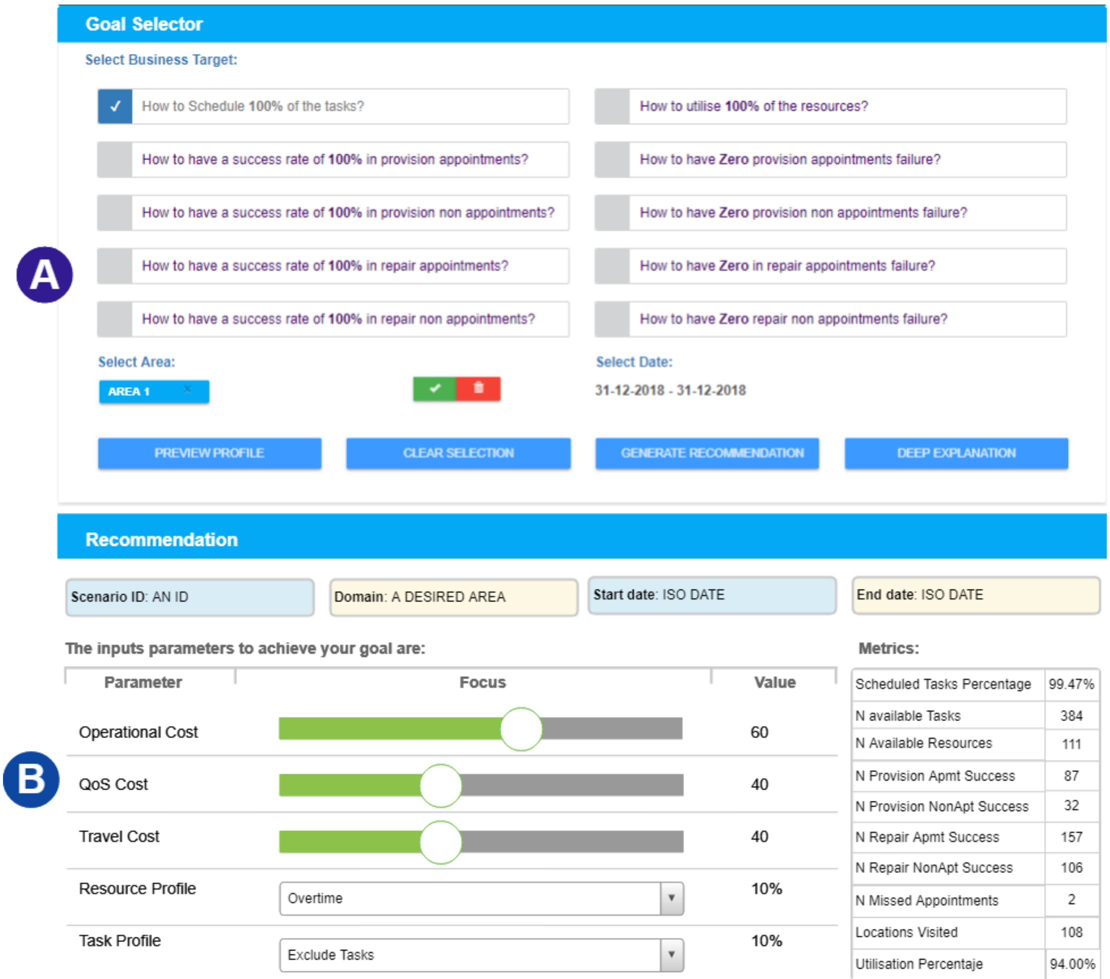

Figure 9.5. The Goal Selector panel (A) and the Recommendation panel (B)

The evaluated inputs and the corresponding rules that contributed to the solution are presented in the explanation panel—this with the capability to analyse the influence of each rule. The supporting view provides information related to the robustness of the model. This includes the level of confidence and relevant metrics related to the knowledge base. The aim is to satisfy some aspects related to safety, causality and bias. Figure 9.6 depicts the explanation panel (C) and the supporting panel.

Figure 9.6. The Explanation panel (C) and the Supporting Panel (D)

The schedule for the skilled staff for a particular scenario is generated and available for planners. Figure 9.7 depicts a schedule overview, and Figure 9.8 illustrates the travel time for transition between tasks.

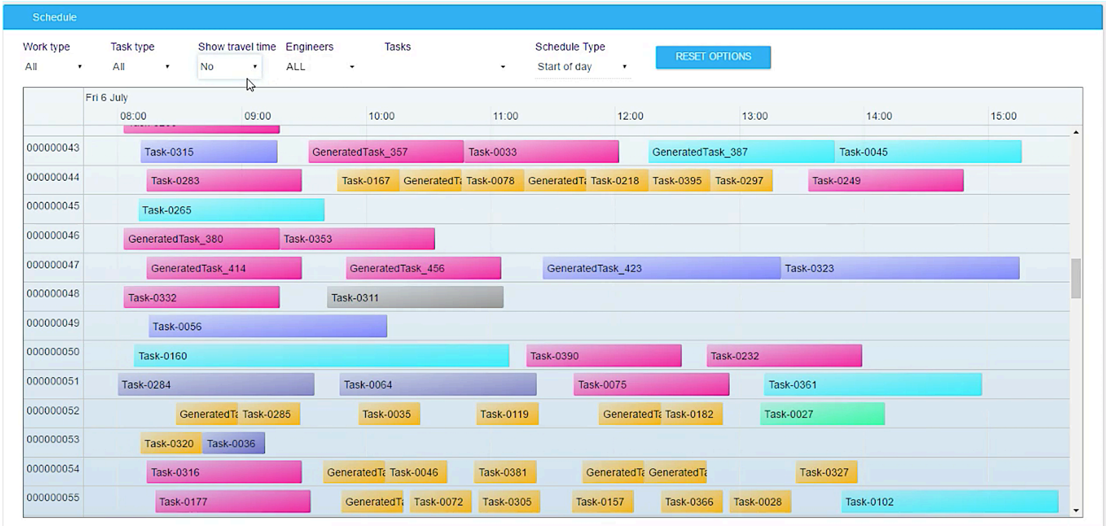

Figure 9.7. Schedule overview for skilled staff

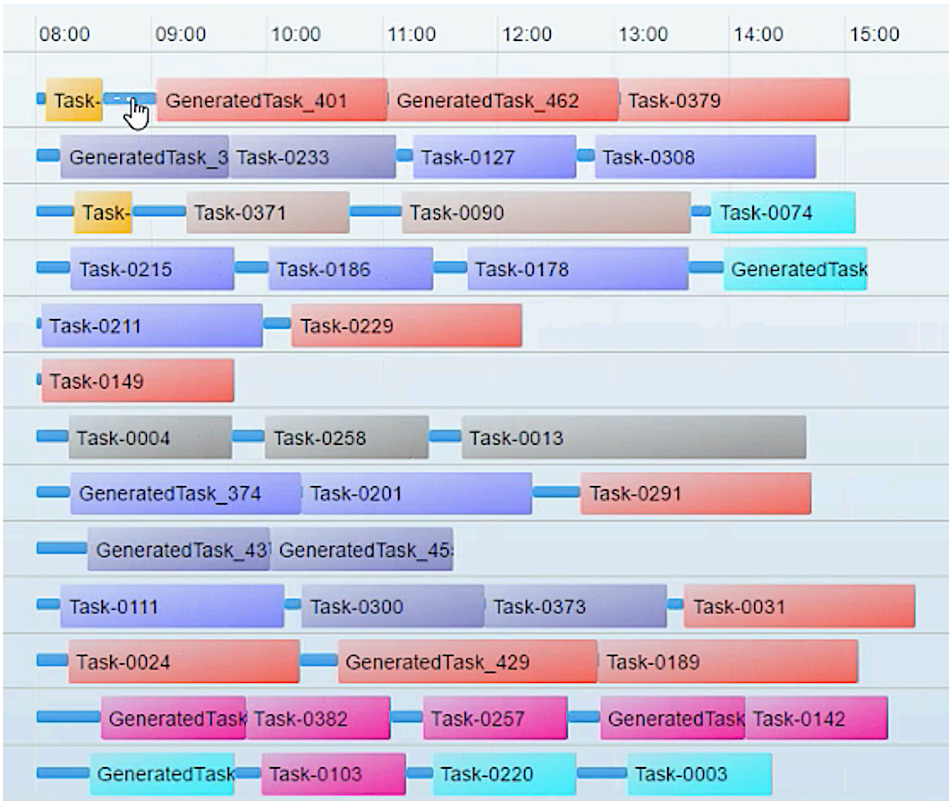

Figure 9.8. The travel transition time between tasks

9.3 GDS framework formalisation

The agile approach implemented in the development of this thesis has enabled incremental enhancements. These improvements focus on addressing identified shortcomings. Each module is the result of tackling the spotted challenges. Figure 9.1 depicts the main modules that support the proposed framework. The aim is to provide an end-to-end solution capable of supporting GDS analysis in field service delivery operations.

Details of each module have been detailed along with this thesis where fuzzy logic is the foundation of the proposal. This framework encompasses the following main components:

1) Business targets selector: This has been detailed in Section 9.2.
2) BB-BC T2 FLS core: This has been developed along with the thesis, the main components are:
    a. Fuzzy rules: These have been detailed in sections 7.3.2 and 8.3.
    b. Similarity evaluation: This has been detailed in Section 8.5.
    c. Solver: As type-2 FLS depicted in Chapter 3, Chapter 7 and Chapter 8.
3) Historic or synthetic data: This has been detailed in Chapter 6.
4) Explanation panel: This has been detailed in Section 9.2.

The outlined XAI framework aims to assist the field service operation by encapsulating the main scheduler systems as a black-box; this strategy has been detailed in Section 6.3.1.

9.3.1 Resource-oriented architecture

The agile modelling approach employed in this thesis has enabled incremental design and iterative enhancements. As a result, each module of the proposed framework for GDS has been developed. Moreover, the system's architecture must be defined in function of interconnectivity among the elements that enable this framework.

Notably, resource-oriented architecture (ROA) is the foundation of data-driven web applications [211]. To succeed in applying resource-oriented design principles each layer and its components encompassing the system must be identified. The fundamental elements of ROA can be summarised as follows [211]:

1) All entities of a system are services;
2) Each service has its properties and contracts; and,
3) Interconnectivity is achieved over the network with a defined location address.

The key benefits of using resource-oriented design are scalability and performance. *Scalability* with ROA is observed mainly by the use of Hypertext Transfer Protocol (HTTP) operations, which release from the use of specific agreements and contracts. *Performance* relates primarily to response times [211]. This section introduces the resulting ROA-based application of the designed GDS system. Figure 9.9 depicts each layer that encompasses the system's architecture and the underlying technology employed for its implementation.

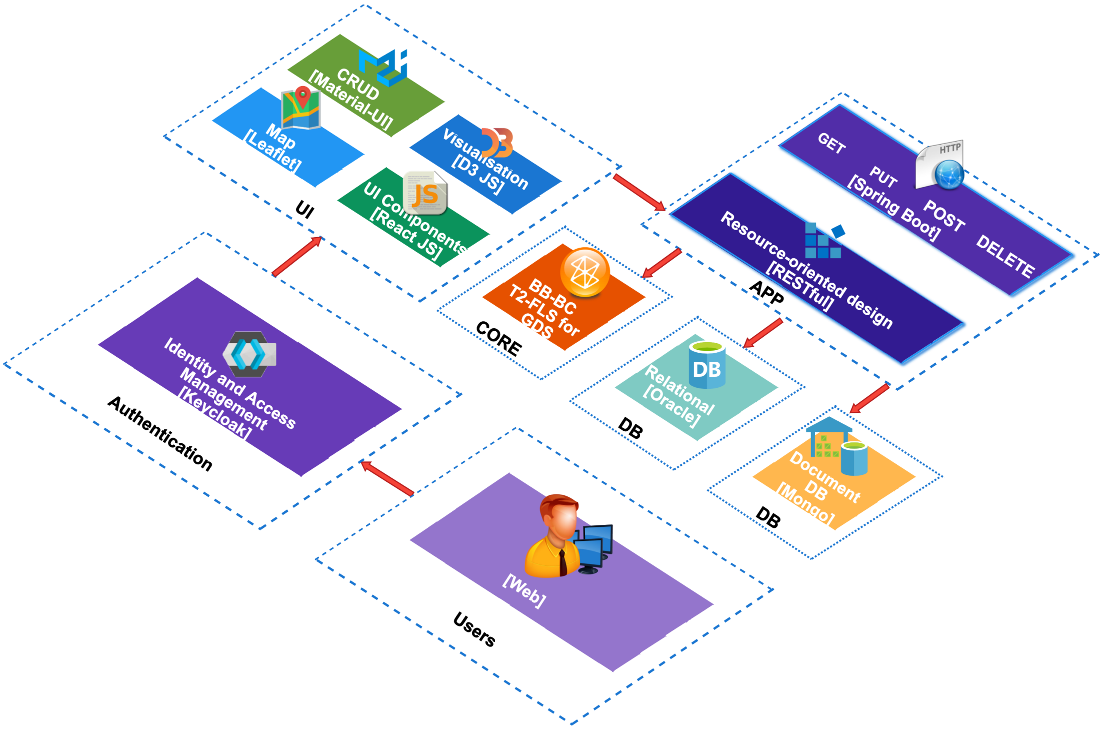

Figure 9.9. The resulting resource-oriented architecture for the BB-BC T2 FLS for GDS

Each layer and their components of the above-mentioned architecture are briefly described as follows:

– *Authentication*: This layer focuses on verifying whether the users have the authorisation to access certain resources. This is implemented with an open-source project that supports a full-fledged authentication and authorisation protocol known as Keycloak[14], which is a solution based on the ROA described above.

– *User interface (UI)*: This layer focuses on the UI by decomposing four main elements, these include: *Maps* – which are implemented by using an open-source JavaScript library for mobile-friendly interactive maps known as Leaflet[15]. *Create, read, update and delete (CRUD) persistent*

[14] https://www.keycloak.org/
[15] https://leafletjs.com/

storage functions – which are implemented by using Material-UI[16], which is an open-source project that facilitates implementing reusable components. *Interactive data visualisations* – these functionalities are implemented with D3.js[17], which is a JavaScript library for producing dynamic, interactive data-driven visualisations in web browsers. And *UI components* – the above-mentioned components are orchestrated using React[18], which is an open-source JavaScript library for building user interfaces or UI components.

- *Application (APP)*: This layer is responsible for interconnecting the UI, the data stores and the core BB-BC T2 FLS for GDS presented in this thesis. This is achieved by implementing web services under the Representational State Transfer (REST) architecture. REST provides interoperability by using HTTP operations such as GET, PUT, POST and DELETE, among others [211]. This layer is implemented with Spring Boot[19], which is an open-source Java-based framework used to create service-based applications.
- *The BB-BC T2 FLS for GDS (CORE)*: This layer is responsible for implementing the framework detailed in this thesis, which is depicted in Figure 9.1. Similarly, this is implemented using Spring Boot.

[16] https://material-ui.com/
[17] https://d3js.org/
[18] https://reactjs.org/
[19] https://spring.io/projects/spring-boot

- *Relational Databases*: As introduced in Section 6.2, this is supported by Oracle[20] and it is used to handle raw data.
- *Documented-oriented Databases*: The developed GDS framework uses document-oriented data structures (see Section 6.2 for a comprehensive review). These use MongoDB[21], which uses JavaScript Object Notation (JSON) documents and schemas.

9.4 Large scale experiment and results

This section extends the experiments to large scale by adding different geographic locations across England. Figure 9.10 provides a high-level view of those locations. These experiments were conducted in two stages. Firstly, training and the next testing. The data set was split randomly in 70% training and 30% testing and is encompasses 326,360 tasks—56% (182,762) corresponding to repair work and 44% (143,598) to provision work. The total estimated duration for this sample is 2,584,184 hours.

The different levels of FOU, the rule length and the rule size were adjusted by the BB-BC algorithm as described in Section 9.1. And the identification of the relevant inputs was conducted by the support of the fuzzy correlation method, as described in Section 8.4. Performance is given by the accuracy achieved through the results, which is confirming the RMSE, as

[20] https://www.oracle.com/uk/database/technologies/oracle-database-software-downloads.html
[21] https://www.mongodb.com/

indicated in Equation (7.40). The business goals studied in this section are reported in Table 9.2.

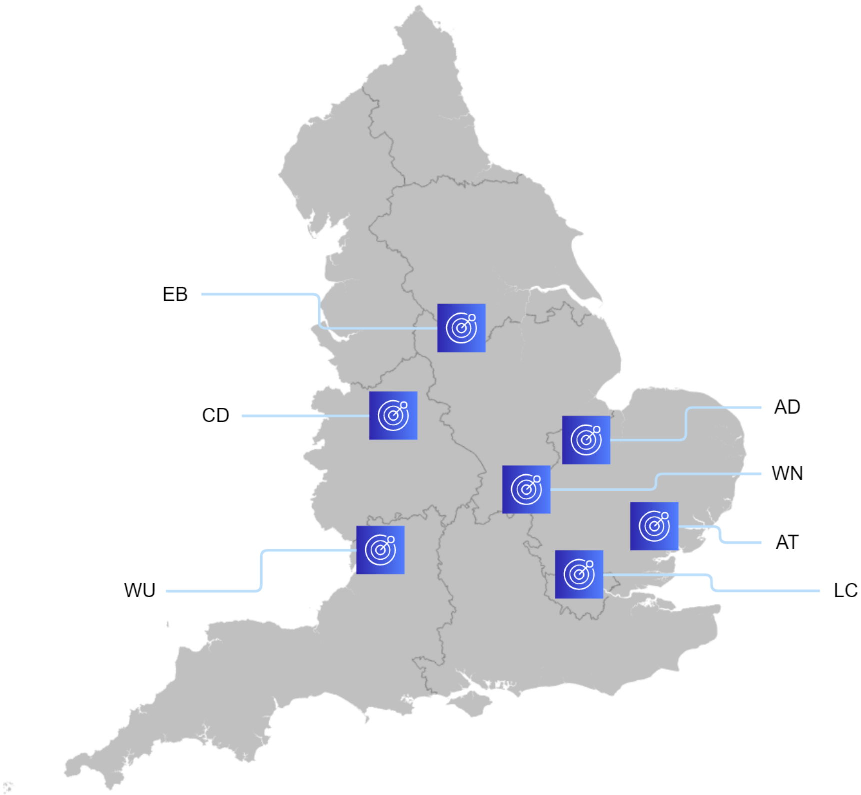

Figure 9.10. Overview of domains based on geolocation

Table 9.2– Business objectives for large scale experiments within the GDS approach.

Goal	Business Goal Description
1	How to schedule 99% of tasks
2	How to achieve a success rate of 97% for Provision Appointments
3	How to utilise 99% of the workforce
4	How to achieve a success rate of 97% for Repair Appointments
5	How to achieve a success rate of 97% for Provision Non-Appointments
6	How to achieve a success rate of 97% for Repair Non-Appointments

9.4.1 Benchmarking

A reference point in measuring the performance of the BB-BC type-2 FLS can be defined by the use of universal approximators such as artificial neural networks (ANNs). A comprehensive overview of ANN was provided in Section 8.6.1. ANNs suit this benchmarking purpose due to their commonly observed performance improvement when more data is available.

Besides, another benchmark instrument can be the generalisation of feedforward ANNs. This generalisation is known as recurrent neural networks (RNNs). RNNs have internal memory; this memory allows processing sequences of inputs related to each other [212]. Therefore, RNNs suit the problem of the study of this thesis. To better benefit from this memory feature, a modified version of RNNs known as long short-term memory unit (LSTM) adds the capability of remembering past data in memory. Hence these two instruments are being employed for performance comparison against the proposed BB-BC type-2 FLS.

To facilitate remembering information for long periods, LSTMs implement three gates. Namely, the forget, input and the output gates. Like any form of RNNs, LSTMs follow a chained architecture, where all modules are linked sequentially. Figure 9.11 illustrates these elements. Walking through the logic of an LSTM can be summarised as follows: first, the forget gate analyses previous output ht-1 and current input x1 and outputs a number in the range of 0 and 1 by employing a sigmoid layer. Therefore, a one indicates to "keep this"; meanwhile, a 0 corresponds to a "forget this". Next, the input gate decides which values will be updated and stored in the cell state by employing a *sigmoid* layer and a *tanh* layer, respectively. Finally, the result is generated in the output gate. This consist of two steps, first by running a sigmoid layer to cell state, then, the cell state passes through a *tanh* layer, and it is multiplied by the output of the sigmoid layer. The LSTM RNN was trained and implemented with Keras[22]. Keras is a Python[23] deep learning library with the ability to run seamlessly on CPU and GPU.

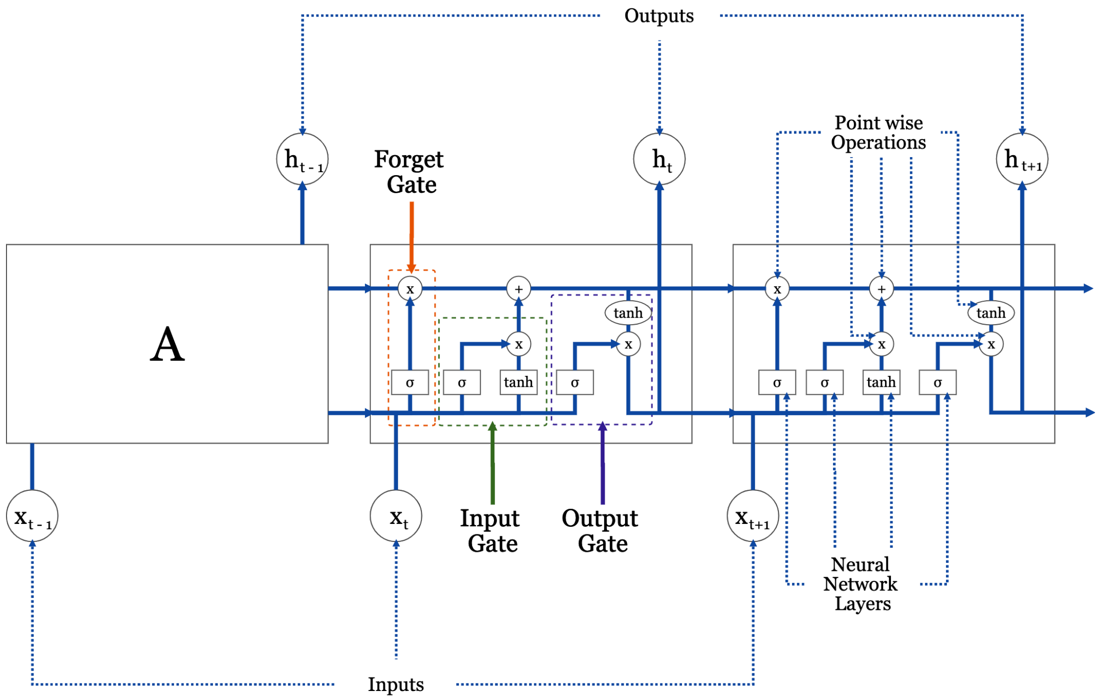

Figure 9.11. Gates present in an LSTM RNN (Source: [212])

9.4.2 Inputs and outputs

The inputs and outputs reported in previous experiments in Table 8.3 are the same and valid for the experiments carried out in this section.

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[22] https://keras.io/
[23] https://www.python.org/

9.4.3 Type-1 and type-2 MFs

Table 9.3 reports a subset of the available parameters with their required values for the Gaussian T1MFs and T2MFs. These membership functions are optimised by the BB-BC approach described in Section 9.1.1.

Table 9.3– Obtained values for Gaussian T1 and T2 MFs generation for {very low, low}.

F	Description	Very Low			Low		
		c	σ	$[\sigma_1, \sigma_2]$	c	σ	$[\sigma_1, \sigma_2]$
R_i	Available resources	6.03	0	[0,3]	30.07	2.47	[1.47, 3.47]
J_i	Available tasks	8.25	10.84	[9.84, 12.84]	71.73	12.37	[11.37, 15.37]
TTH_i	Actual total travel hours spent	19.34	13.17	[11.17, 14.17]	90.23	6.88	[4.88, 9.88]
TJH_i	Actual total task hours spent	64.82	39.78	[37.78, 41.78]	369.72	16.75	[15.75, 19.75]
TPA_i	Actual total provision appointment	2.73	3	[1,5]	74.05	10.81	[7.81, 13.81]
MHA_i	Man-hours allocated	10.77	12.16	[9.16, 13.16]	160.23	14.05	[11.05, 16.05]
PAS_i	Provision appointment success	2.50	3.05	[2.05, 5.05]	73.24	9.25	[7.25, 11.25]

Table 9.4 reports a subset of the available parameters with their values for the Gaussian T1MFs and T2MFs. These membership functions are optimised by the BB-BC approach described in Section 9.1.1. Figure 9.12 illustrates selected examples of the resulting clustering with five linguistic terms. Similarly, Figure 9.13 depicts the Gaussian T2MF for the available resources parameter.

Table 9.4– Values for Gaussian T1 and T2 MFs generation for {medium, high, very high}.

F	Medium			High			Very High		
	c	σ	$[\sigma_1, \sigma_2]$	c	σ	$[\sigma_1, \sigma_2]$	c	σ	$[\sigma_1, \sigma_2]$
R_i	105.57	1.86	[0.14, 3.86]	114.27	2.56	[0.56, 4.56]	122.34	3.54	[1.54, 6.54]
J_i	345.34	22.85	[19.85, 23.85]	397.22	19.62	[17.62, 22.62]	504.16	49.6	[48.6, 52.6]
TTH_i	113.82	6.89	[3.89, 7.89]	140.40	6.78	[5.78, 7.78]	164.84	8.2	[7.2, 10.2]
TJH_i	430.16	17.04	[14.04, 19.04]	495.16	13.3	[12.3, 16.3]	544.22	14.07	[11.07,16.07]
TPA_i	106.17	6.9	[3.9, 7.9]	135.01	8.62	[6.62, 11.62]	184.65	9.45	[6.45, 10.45]
MHA_i	236.44	14.31	[12.31, 16.31]	872.96	30.87	[29.87, 33.87]	968.13	38.07	[37.07,41.07]
PAS_i	102.51	6.21	[3.21, 9.21]	125.31	7.39	[6.39, 10.39]	159.38	11.07	[10.07,13.07]

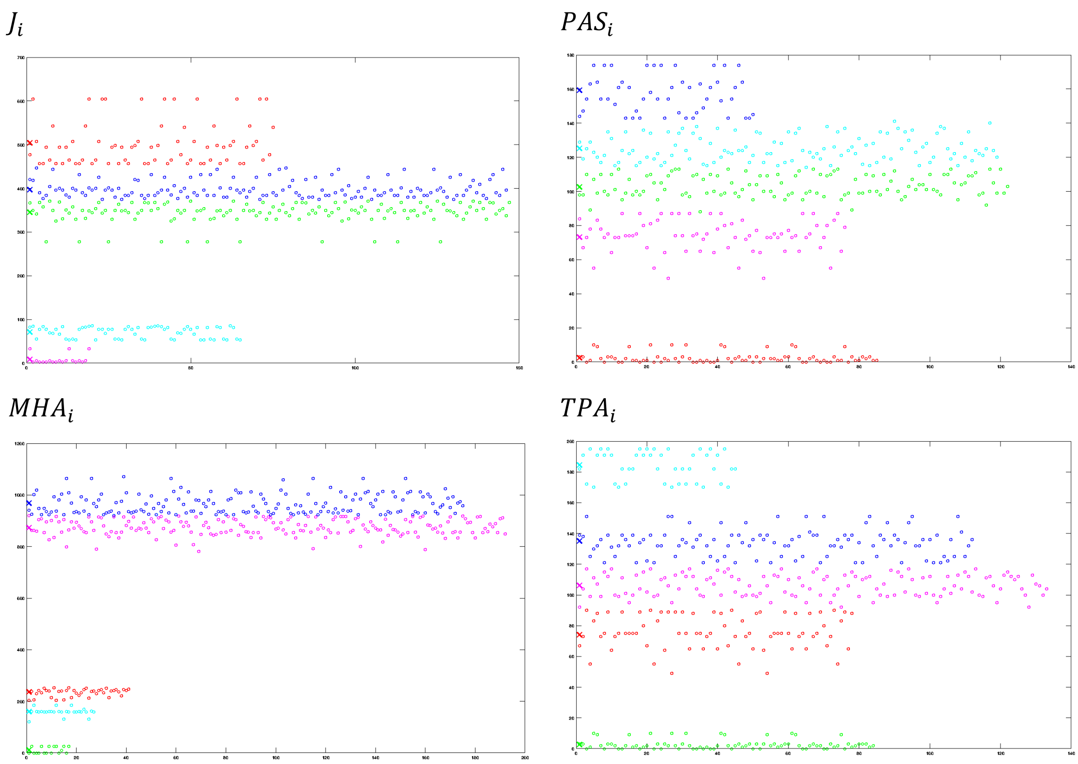

Figure 9.12. Example of clustered data with five linguistic terms

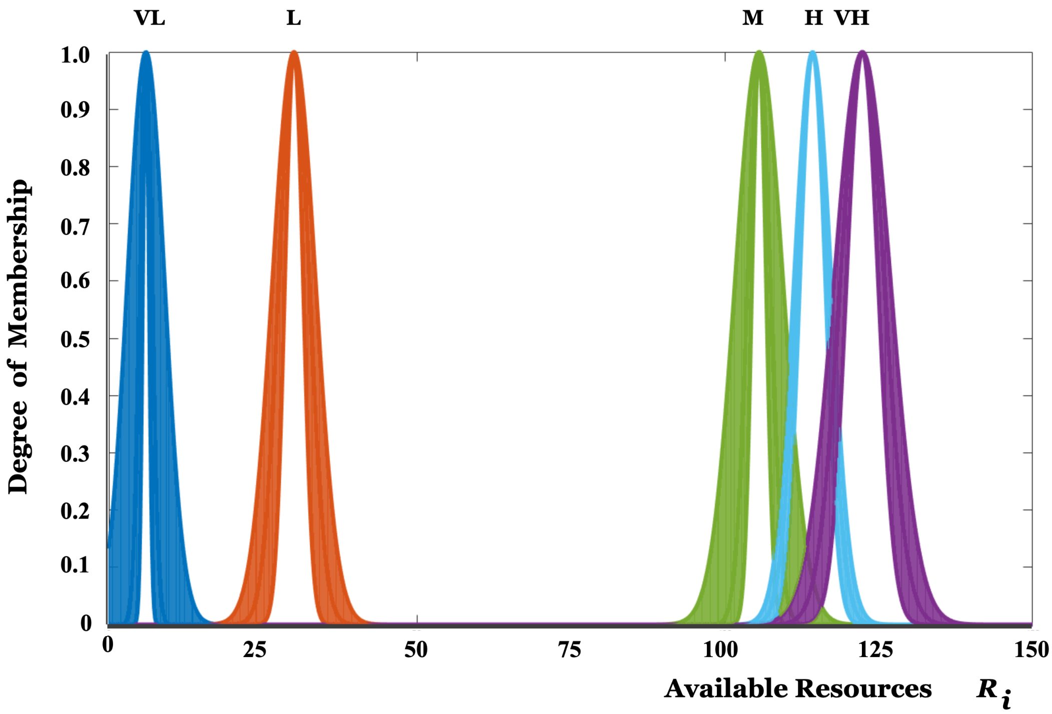

Figure 9.13. Gaussian T2MFs for available resources R_i parameter

9.4.4 Fuzzy rules for each business goal

The fuzzy rules are optimised by the BB-BC approach described in Section 9.1.1. For brevity, Table 9.5 reports an extract of the rule base for Goal 1 from a total size of 45 rules. Analogously, a subset of the rule base for Goal 2, is reported in Table 9.6 from a total size of 39. A subset of the rule base for Goal 3 is reported in Table 9.7 from a total of 25 rules. Similarly, a subset reflecting the rules for Goal 4 is presented in Table 9.8 from a total of 27 rules. Correspondingly, a subset of rules referring to Goal 5, is reported in Table 9.9. Finally, a subset of rules for Goal 6 is presented in Table 9.10 from a total of 23 rules.

Table 9.5–Extract of rule base for Goal 1, from a total size of 45 rules.

Rule Index	IF Antecedents			THEN Consequents		
	R_i	J_i	WT_i	PJS_i	PAS_i	RAS_i
1	Very Low	Low	Low	Low	Low	Very Low
4	Low	Very Low	High	High	Low	Very Low
7	Low	Medium	Medium	Medium	Medium	Low
11	Very Low	High	Low	Low	High	Very Low
15	Low	Very High	High	High	High	Low
19	Medium	Low	Medium	Medium	Low	Medium
23	Medium	Medium	Very Low	Low	Low	Medium
33	Medium	Very High	Medium	Medium	High	Medium
36	Very High	Low	Low	Low	Medium	High
39	High	Low	High	High	Low	Very High
42	High	Medium	Medium	Medium	Medium	High
45	Very High	High	High	High	High	Very High

Table 9.6– Extract of rule base for Goal 2, from a total size of 39 rules.

Rule Index	IF Antecedents			THEN Consequents	
	R_i	J_i	$PPAS_i$	$MSRA_i$	PAS_i
1	Low	Low	Low	Low	Low
3	Very Low	Very Low	High	High	Low
5	Very Low	Medium	Medium	Medium	Medium
7	Low	High	Low	Low	High
11	Medium	High	High	High	Very High
14	Very Low	Low	Medium	Medium	Low
17	Medium	Medium	Low	Low	Medium
21	Medium	Medium	High	High	Medium
24	Medium	High	Medium	Medium	High
26	High	Low	Low	Very Low	Low
29	Very High	Medium	High	Very High	Medium
33	Very High	Medium	Medium	Medium	Medium
35	High	High	Low	Very Low	Medium
37	High	Very High	Very Low	Medium	High
39	High	High	Very High	High	Medium

Table 9.7– Extract of rule base for Goal 3, from a total size of 25 rules.

Rule Index	IF Antecedents			THEN Consequents	
	R_i	J_i	PRU_i	MHA_i	$SSRA_i$
3	Very Low	High	High	Very High	Medium
5	Low	Medium	Medium	Medium	Medium
7	Very Low	Very High	Low	Low	High
8	Low	High	High	High	High
10	Medium	Low	Medium	Medium	Low
13	Medium	High	Very High	Medium	High
15	Medium	Low	Low	Low	Medium
17	High	Low	High	High	Low
19	High	Medium	Medium	Medium	Medium
23	High	Medium	Low	Medium	High
25	Very High	High	High	High	High

Table 9.8–Rule base for Goal 4, with a total size of 27 rules.

Rule Index	IF Antecedents			THEN Consequents	
	R_i	J_i	$PRAS_i$	$MSRA_i$	RAS_i
1	Very Low	Low	Very Low	Low	Low
2	Very Low	Low	Medium	Medium	Low
4	Low	Medium	Low	Low	Low
6	Low	Medium	High	High	High
8	Low	High	Medium	Medium	Medium
9	Low	High	Very High	Medium	High
11	Medium	Low	Medium	Medium	Medium
13	Medium	Medium	Low	Low	Low
15	Medium	High	High	High	High
17	Medium	High	Medium	Medium	Medium
19	High	Low	Low	Low	Low
21	High	Low	High	High	High
23	High	Medium	Medium	Medium	Medium
25	High	High	Low	Low	Medium
26	High	High	Medium	Medium	Medium
27	Very High	Very High	Very High	Very High	Very High

Table 9.9– Extract of rule base for Goal 5, from a total size of 32 rules.

Rule Index	IF Antecedents			THEN Consequents
	R_i	J_i	$PPAS_i$	$MSRA_i$
1	Very Low	Very Low	Very Low	Very Low
3	Low	Low	High	High
5	Very Low	Medium	Medium	Medium
7	Low	High	Low	Low
9	Low	Very High	Very High	Very High
11	Medium	Low	Medium	Medium
13	Medium	Medium	Low	Low
15	Medium	Medium	High	Medium
17	Medium	High	Medium	Medium
19	High	Low	Low	Medium
21	Very High	Medium	High	Very High
23	High	Medium	Medium	Medium
25	High	High	Low	Low
27	High	Very High	Very High	Very High

Table 9.10– Extract of rule base for Goal 6, from a total size of 23 rules.

Rule Index	IF Antecedents			THEN Consequents
	R_i	J_i	$PPAS_i$	$MSRA_i$
1	Very Low	Low	Low	Low
4	Low	Medium	Low	Low
6	Low	Medium	High	High
8	Medium	Low	High	High
10	Medium	Medium	Medium	Medium
12	Medium	High	High	High
14	Medium	High	Very High	High
16	High	Low	Medium	Medium
18	High	Medium	Low	Low
20	Very High	Medium	High	High
23	Very High	High	Medium	High

9.4.5 Results

This section focuses on extending the testing to other geographical areas while evaluating the optimisation enhancements detailed in the aforementioned sections. Each of the learning and testing phases for every goal encompassed 1,000 evaluation cycles. The employed computing equipment is a virtual machine (VM) with a 64-bit processor at 1.7 GHz quad-core and a maximum of 8 GB total available random-access memory (RAM). Figure 9.14 reports the data volume for the different phases of this incremental modelling.

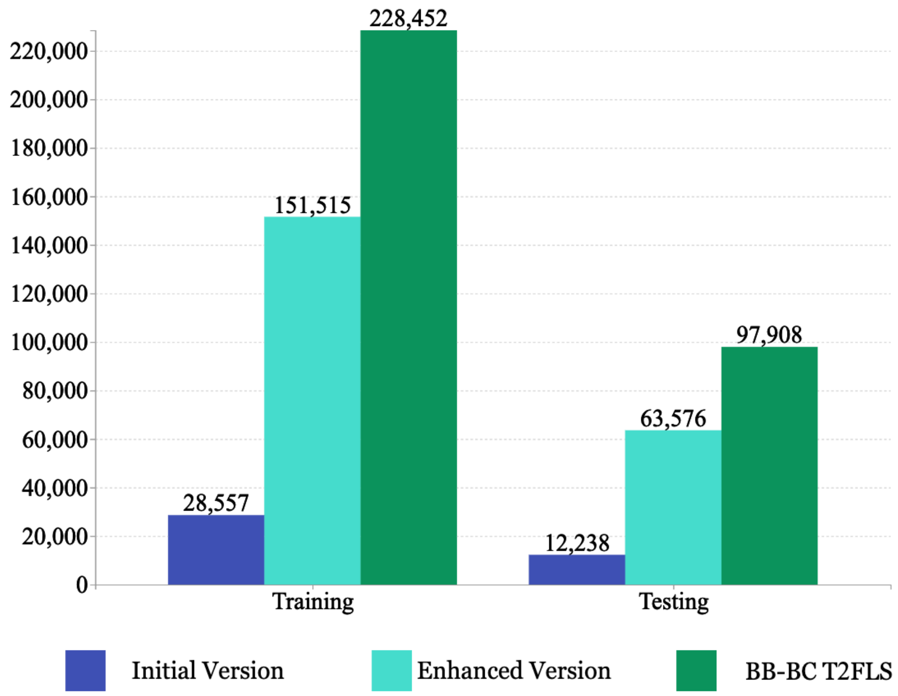

Figure 9.14. Data volume in the different stages of agile development

Figure 9.15 depicts the maximum distribution of time in milliseconds for the training phase. On average, the training clocked time was 2.15 minutes in the initial version, and 7.10 minutes in the enhanced version, and 10.61 minutes in the BB-BC T2FLS. This increment is due to the additional optimisation features. In addition, the number of rules in each version of the model is reported in Figure 9.16. As can be observed, on average the BB-BC reported a reduced number of rules compared with their initial counterpart version and enhanced version, respectively.

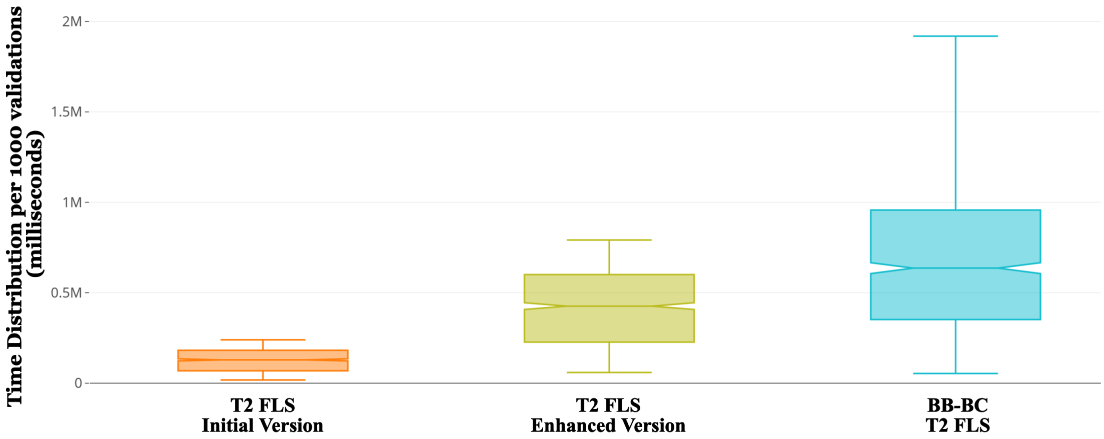

Figure 9.15. Data volume in the different stages of agile development

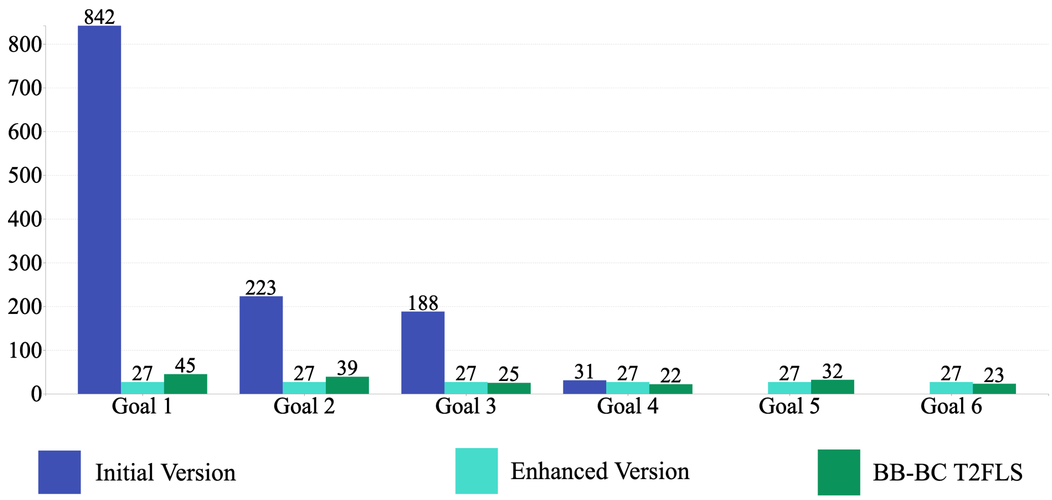

Figure 9.16. Data volume in the different stages of agile development

As indicated in Equation (7.40), the RMSE is employed to evaluate the obtained results. The closer the RMSE is to zero, the better the performance in the experiments. Table 9.11 and Table 9.12 report the performance for training and testing, respectively. In the context of training, it can be observed that the ANN and the and LSTM RNN perform similarly. Overall, ANN, outperformed its counterpart LSTM RNN, BB-BC T2FLS and type-1 FLS by 3%, 35% and 49%, respectively. Detailed performance breakdown per each domain can be consulted in Appendix C.

Table 9.11– Average RMSE comparison among each geolocation, in the training phase.

Geo-location	Training			
	Type-1 FLS	**BB-BC T2FLS**	**ANN**	**LSTM RNN**
Avg. AT	0.73949823	0.55799017	0.37638027	0.38646408
Avg. EB	0.74689322	0.56914997	0.38014407	0.39535276
Avg. CD	0.76168318	0.57193992	0.38052045	0.39593245
Avg. WU	0.75059071	0.75328673	0.38390787	0.39767154
Avg. AD	0.7542882	0.57417188	0.38390787	0.39419337
Avg. WN	0.7528092	0.567476	0.38202597	0.39728508
Avg. LC	0.7535487	0.56914997	0.38014407	0.39805801
Global Average	**0.7513302**	**0.594737806**	**0.381004367**	**0.394993899**

In the context of testing, it can be observed that the ANN and the and LSTM RNN perform similarly. Overall, LSTM RNN outperformed its counterpart ANN, BB-BC T2FLS and type-1 FLS by 13%, 50% and 57%, respectively. Detailed performance breakdown per each domain is available in Appendix C.

Table 9.12– Average RMSE comparison among each geolocation, in the testing phase.

Geo-location	Testing			
	Type-1	**BB-BC T2FLS**	**ANN**	**LSTM RNN**
Avg. AT	0.69305878	0.57290086	0.34278182	0.29380948
Avg. EB	0.69998937	0.58435888	0.34620963	0.3005671
Avg. CD	0.71385055	0.58722338	0.34655242	0.30100782
Avg. WU	0.70345467	0.77341616	0.34963745	0.30232996
Avg. AD	0.70691996	0.58951498	0.34963745	0.29968567
Avg. WN	0.70553384	0.58264017	0.34792354	0.30203615
Avg. LC	0.7062269	0.58435888	0.34620963	0.30262377
Global Average	**0.7041477**	**0.610630473**	**0.346993134**	**0.300294279**

However, because of the black-box nature of ANNs and deep learning approaches the degree of interpretability is a known issue. Consequently, the effectiveness among the compared methods must achieve simultaneously two important factors, there are performance and certain degree of interpretability, hence the preference for the GDS approach.

Moreover, in real-world applications it is more important that a system is both scalable and return sensible results, than a system which performs better but does not offer clear mechanisms for scalability nor interpretability. The next section will highlight the benefits of the achieved BB-BC T2 FLS.

9.5 On carbon footprint from field service operations

In the UK, BT has a fleet size of nearly 34,000 vehicles, which generates two-thirds of BT's operational carbon emissions [213]. Various efforts have been incorporated to minimise this carbon footprint including the use of electric vehicles (EVs), among others. With a fleet of the aforementioned size, EV adoption is challenging due to the need for a significative investment. This is observed in the 23 EVs trialled during 2019/2020 and the plans to add 46 EVs more to the fleet during 2020 [213]. Hence, these figures strengthen the importance of the capabilities of this solution in this matter.

As introduced in Section 6.3.4, each simulated scenario provides certain metrics, which allow the computation of performance indicators. In this context, this solution enables the simulation of long periods for desired geographical locations. Figure 9.10 introduced the selected domains for these experiments. To review the capability of this solution in the carbon emissions analysis from field service operations, let us study the following two metrics: "travel hours spent" and "task hours spent".

"*Travel hours spent*" refers to the number of hours that an engineer employs to travel to the consumer premises. Similarly, "*task hours spent*" denotes the actual time spent while carrying out the job until it is completed. As introduced in Section 6.2.3, the pattern discovery approach implemented in this thesis allows identifying detailed granularity of CO_2 emissions by various verticals including speed profiles, geographical domain carbon footprint distribution and the relationship between travel distance and travel time. Therefore, this approach can also be applied to analyse the GDS results.

It is noteworthy to point out that contrary to systems that generate solutions under the optimality umbrella where the results rarely meet turbulent real-life environments, in the proposed GDS, the results are aligned with the desired business targets. Consequently, it can be observed the effect of this approach in the above-mentioned metrics. Where a minimised number of hours spent on travelling benefit the footprint emissions minimisation aim. To illustrate this, Figure 9.17 reports the hours spent on travelling to consumer premises and the hours spent on completing jobs for a calendar year simulation including a total of 306 days for the geographical domain referred as "AT" (see Figure 9.10 for geolocation reference), this, by applying the proposed GDS approach.

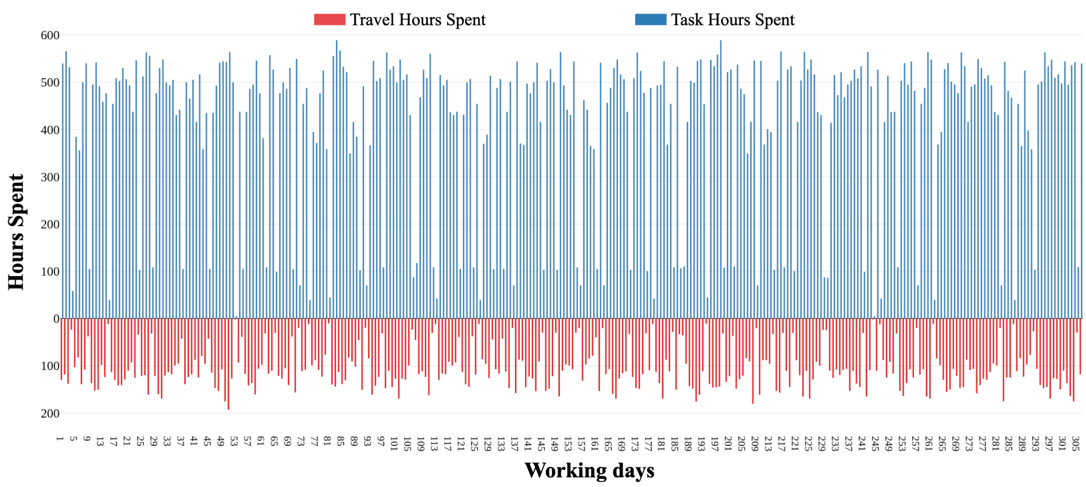

Figure 9.17. Travel and task hours spent for a year simulation within the GDS approach in the geographical domain denoted as "AT"

For brevity, Table 9.13 reports the comparison between these simulation metrics, obtained within the GDS approach, and without it. Where the seven geographical domains are listed by using the above-mentioned abbreviations introduced in Figure 9.10. The column entitled *Measure*, reports each relevant metric for this review. Finally, the *CO_2 reduction* row reports the percentage of carbon emissions minimisation for this simulation exercise.

Table 9.13– Comparison metrics between GDS and conventional simulation.

Type	Measure	Geographical Domain						
		AT	**EB**	**CD**	**WU**	**AD**	**WN**	**LC**
GDS	Total Travel (Hrs.)	32,401	48,226	69,851	39,530	49,191	78,223	79,798
	Avg. (Hrs.)	106	158	228	129	161	256	261
	SD (Hrs.)	45	67	97	55	68	108	111
	Distance (Mi.)	421,219	626,943	908,064	513,887	639,481	1,017,031	1,037,372
	Total CO_2 (m tonnes)	229	341	494	279	348	553	564
NO-GDS	Total Travel (Hrs.)	33,600	50,589	73,623	41,230	51,503	81,284	84,231
	Avg. (Hrs.)	110	165	241	135	168	266	275
	SD (Hrs.)	47	70	102	57	71	113	117
	Distance (Mi.)	436,804	657,663	957,099	535,984	669,537	1,056,695	1,095,004
	Total CO_2 (m tonnes)	238	358	521	291	364	575	596
CO_2 Reduction		**3.78%**	**4.74%**	**5.18%**	**4.12%**	**4.39%**	**3.82%**	**5.36%**

As can be observed, this tool is capable of modelling a reduction between 3.78% and 5.36% of footprint carbon emission due to travel times for jobs completion on customer premises for specific geographical areas. In practice, this translates to a reduction of 135 metric tonnes of CO_2 for the selected domains.

Moreover, the data exploration capability incorporated in Section 6.2.2 facilitates analysing the impact of carbon footprint by geographical domain breakdown and time slots. For example, Figure 9.18 depicts two graphical representations of CO_2 emissions profiles for a given geographical area. As can be noticed, the picture in the left reports higher emissions in comparison with its right picture counterpart. This is expected because the left side reflects the traffic conditions between 7 – 9 hrs while the right side illustrates the traffic conditions between 11 – 13 hrs.

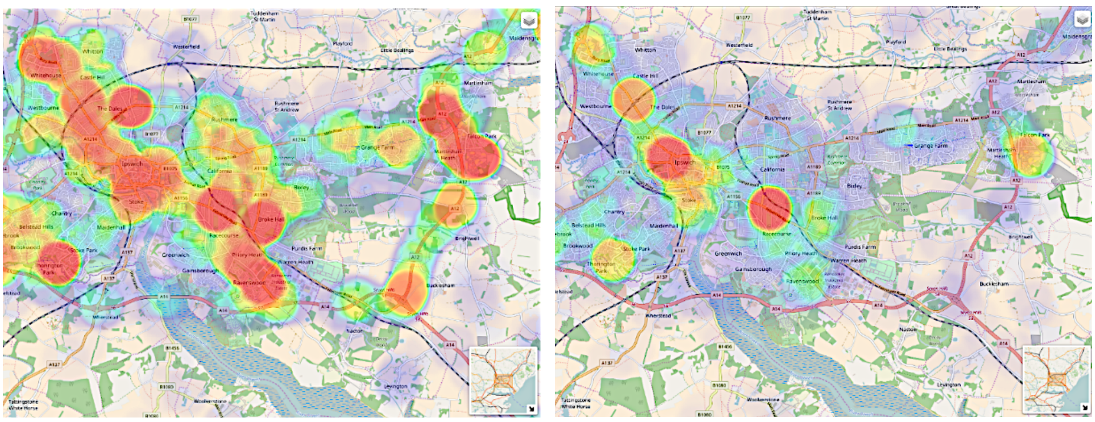

Figure 9.18. Carbon footprint visualisation. (Left) 7 am to 9 am. (Right) 11 am to 1 pm

The relevance of this visualisation is that CO_2 emissions relate to the company's field service operational activity, where the highlighted areas denote the transited routes by the BT fleet. Coloured areas represent higher CO_2 emissions. The colouring threshold is adjusted in function of the desired granularity by employing three ranges, namely, low, medium and high. Each threshold is computed as follows: $t_{low} = x\,[min, \mu - \sigma^2]$, $t_{medium} = x\,[\mu - \sigma^2, \mu + \sigma^2]$ and $t_{high} = x\,[\mu + \sigma^2, max]$. Where x denotes the CO_2 value to be represented, min refers to the minimum CO_2 value recorded, μ is the CO_2 mean, σ^2 denotes the standard deviation of the CO_2 recordings and max corresponds to the higher recorded value for the carbon footprint in that time slot.

9.6 On productivity for end-to-end field delivery

The end-to-end flow implemented in this target-oriented framework enables faster simulation capability. On average, simulation scenarios can be generated 13 times faster than conventional approaches, this was observed and reported in Section 6.2.1. In this context, Figure 6.2 depicted that this improvement was first enabled by the use of document-based data structures instead of relational paradigms. However, the incremental development of this GDS approach focused on leveraging this feature to support the whole simulation framework. As a result, the effect on productivity can be observed in a vital metric, namely, "right first-time".

The *right first*-time metric refers to succeeding in completing the job at the first attempt. The proposed target-oriented approach enables planners and managers to project this metric in the function of the desired goal being sought. The right first-time metric can be computed as the ratio encompassing successful and failed jobs. In this context, Figure 6.18 and Figure 6.19 presented the different measures involved in the aggrupation of success and failure simulation results.

For brevity, Table 9.14 reports the average comparison between this GDS approach and conventional methodologies for a calendar year simulation including a total of 306 working days, which encompass 48 Mondays, 52 Tuesdays, 52 Wednesdays, 53 Thursdays, 49 Fridays and 52 Saturdays. As depicted in Figure 6.11 the proposed framework enables this day-by-day granularity.

Table 9.14– Average comparison between success and failure job completion simulation.

Geo-location	Within GDS		Without GDS		Avg. Improvement (%)
	Success (%)	Failure (%)	Success (%)	Failure (%)	
Avg. AT	90.83	9.17	88.84	11.16	2.24
Avg. EB	91.20	8.80	89.05	10.95	2.41
Avg. CD	92.86	7.14	89.87	10.13	3.33
Avg. WU	92.30	7.70	90.07	9.93	2.48
Avg. AD	92.19	7.81	89.95	10.05	2.49
Avg. WN	92.56	7.44	90.23	9.77	2.58
Avg. LC	91.54	8.46	89.18	10.82	2.65
Global Average	**91.93**	**8.07**	**89.60**	**10.40**	**2.60**

As can be observed, the proposed GDS approach enables a productivity increase of 2.6%, on average. In practice, this contributes to overall customer satisfaction measurements that refer to keeping to appointment times, completing orders in the promised timeframe or fixing faults when agreed.

It is noteworthy to point out that other factors such as the percentage of the workforce utilisation and the allocated man-hours do not necessarily reflect the outcome of the job completion, therefore, these elements have been excluded of this productivity analysis.

9.7 On customers' perception of BT service delivery

Undoubtedly, a factor that impacts customers' perception of enterprises is customer satisfaction based on the received service. In the context of field service delivery, this customer satisfaction can be measured by the Net Promoter Score (NPS) [147]. The NPS focuses on a single assessment: *"how likely is that the customer would recommend our company to a friend or colleague?"*. The popularity of the NPS is due to its simplicity, which allows identifying promoters and detractors.

In practice, an element that stands out among the factors that influence the field service operations is the fact of missing appointments. A *missed appointment* can be observed when an engineer does not meet the appointment at the customer premises. Beyond the potential reasons for this phenomenon, the resulting outcome is a poor customer experience, consequently, this element impacts the NPS.

With the proposed GDS approach, planners can anticipate the number of missed appointments. In this context, let us assume that a missed appointment results in a confirmed detractor. Therefore, minimising the number of missed appointments is fundamental for aspiring to score better in the NPS. Table 9.15 reports a calendar year simulation including a total of 306 working days for the seven geolocations studied in these experiments.

As can be observed, for the studied geographical areas the GDS approach provides an overall improvement on the number of missed appointments of 1%, on average.

It is noteworthy to point out that this customers' perception analysis is by no means exhaustive. In other words, the simplicity of this approach facilitates positioning the GDS approach and its capabilities to handle low-level operational granularity and deliver actionable insight, which enables evaluating decisions before acting.

Table 9.15– Number of missed appointments comparison.

Geo-location	Number of missed appointments		Improvement (%)
	Within GDS	Without GDS	
Avg. AT	2,948	2,972	0.8%
Avg. EB	3,012	3,032	0.7%
Avg. CD	2,745	2,770	0.9%
Avg. WU	2,994	3,034	1.3%
Avg. AD	3,175	3,209	1.1%
Avg. WN	2,867	2,899	1.1%
Avg. LC	2,903	2,932	1.0%
Global Average	**2,949**	**2,978**	**1.0%**

9.8 Benefits of the BB-BC T2 FLS for GDS

An optimised version capable of supporting GDS problems is achieved and demonstrated in this chapter. In practice, its main benefits can be listed as follows:

1) Three dimensions of optimality. First, the number of rules is minimised, even if the number of linguistic labels increases with respect to the previous version presented in Chapter 8 -. Second, the number of antecedents at rule level is minimised; this facilitates explanations self-driven by users by employing the visualisation tool introduced in Section 9.2. Third, the footprint of uncertainty is optimised across all fuzzy sets. This addresses one of the shortcomings spotted in the enhanced version presented in the previous chapter.
2) Simulation capability. This, in the function of performance metrics, simulation size, performance requirements and scenarios covered. A robust system is more capable of scaling. This has been demonstrated incrementally along with the three versions of the proposal, which were introduced chronologically in Chapter 7, Chapter 8 and this chapter, respectively.
3) Component performance. This, in the function of the performance of every single architectural element of the simulation system. As has been demonstrated, each module being added to the incremental modelling delivers value and either they address challenges or enhance performance.

4) Analysis before real-life decision making. The framework developed in this thesis allows analysing scenarios and the effects of pursuing desired business targets before implementing in real-life operations. This is vital to assess portfolio configurations and the effect in daily operations. By creating and analysing scenarios, now planners can see in advance whether a decision will be efficient and effective in an environment that is focused on the relevant parameters that influence the operation. In this context, Figure 9.19 illustrates an interface of BT's Field Scheduler. As can be observed, the system is designed to optimise schedules and provide the best configuration. At some degree, that configuration is theoretical, and it does not include uncertainty that is inherent in the operation. The proposed GDS model embeds this from the data and allows to set realistic goals, that are more likely to be achieved.
5) Visual analytics as supporting tools. It has been showcased in the various elements of this framework the use of visualisations as the mechanism to facilitate communication, to enhance interpretability and transparency. In practice, this releases users from understanding mathematical and heuristic techniques that provide optimal solutions. Moreover, the modularity approach employed as part of the agile modelling reduces cognitive load. For example, Figure 9.20 and Figure 9.21 illustrate this challenge. Where changing the priority of a task or committing to a specific time window enable various configurations (see lateral panels) that add complexity and limit exploration, and delay

action. Hence, the benefit of the BB-BC T2 FLS for GDS developed in this work.

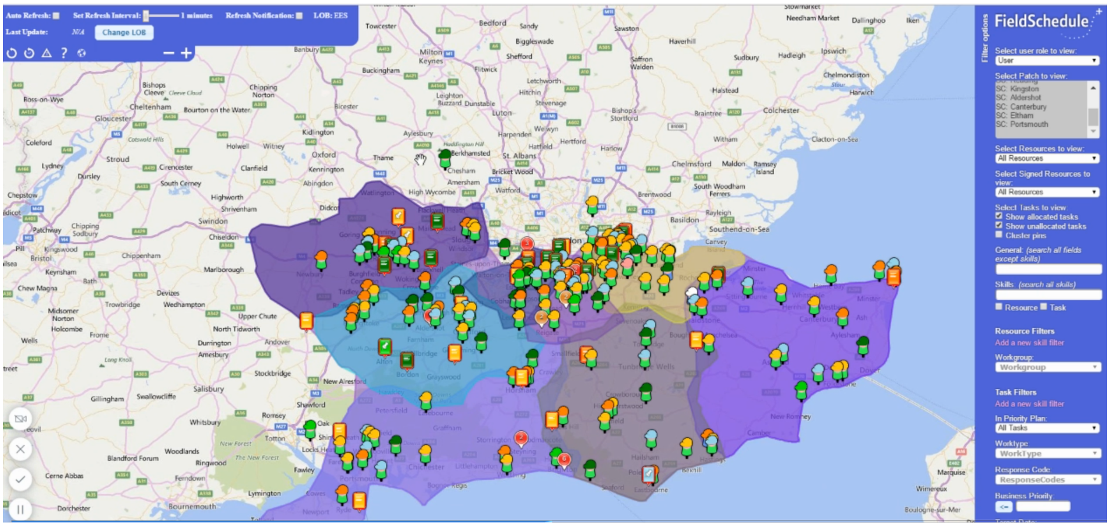

Figure 9.19. Example of working areas and engineer's distribution within BT's Field Scheduler (© BT Plc)

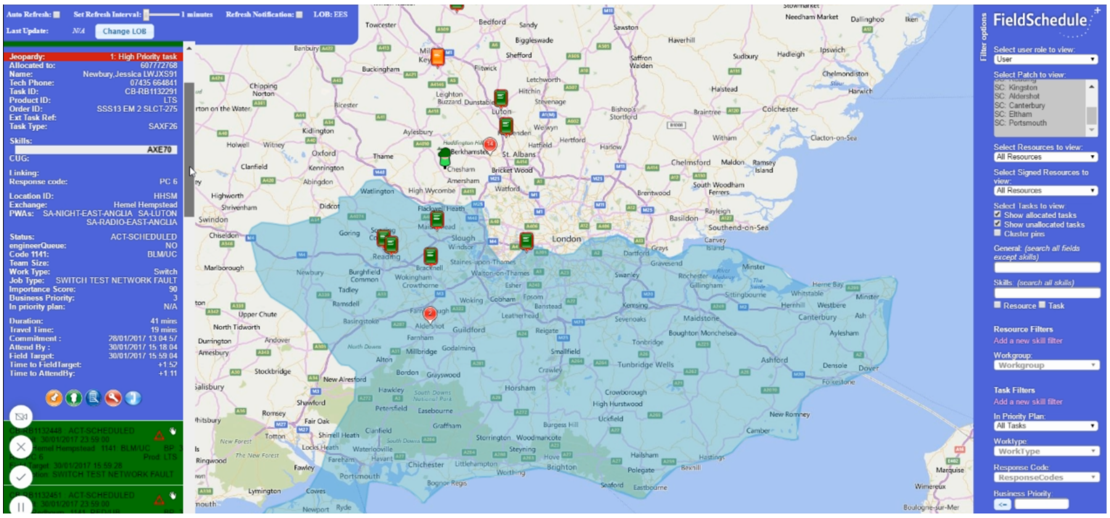

Figure 9.20. Example of change of priority in a task within BT's Field Scheduler (© BT Plc)

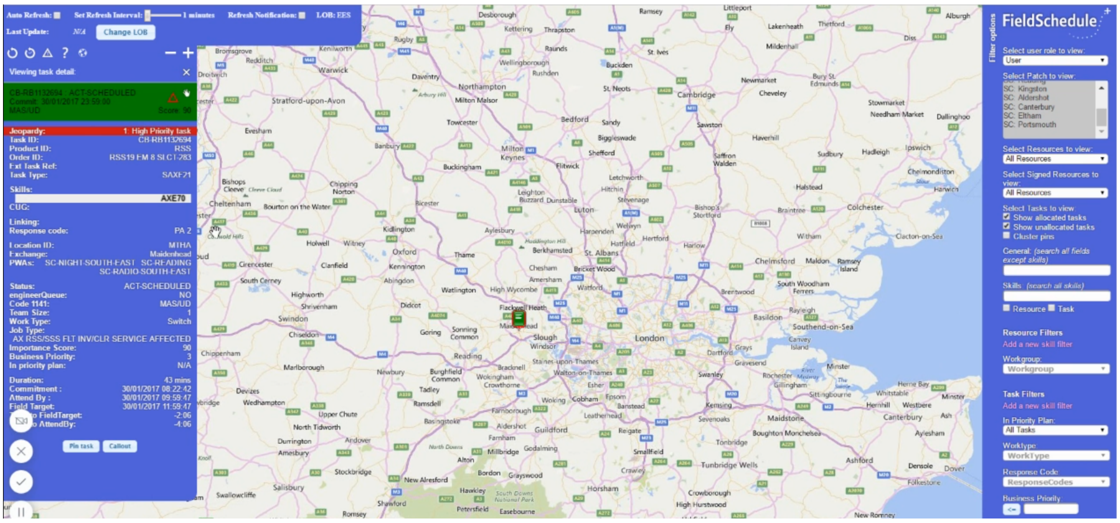

Figure 9.21. Example of one task committed to a specific time window within BT's Field Scheduler (© BT Plc)

9.9 Discussion

This chapter has introduced an optimisation methodology based on the BB-BC algorithm and outlined the use of visualisation techniques to depict the underlying decision made by the model. Successively, this chapter formalised the GDS framework by outlining the main modules, which were detailed during the development of this thesis. Subsequently, this chapter defined the set up for large scale experiments, including seven different geographical areas within the UK territory. Next, this chapter introduced an additional element for benchmarking, and it provided the resulting optimised values for Gaussian T1 and T2 MFs for five linguistic labels. Successively, this chapter presented extracts of the rules for each business goal. Finally, this chapter reported the results and the benefits of the achieved model.

Each section of this chapter has devoted to providing a detailed insight into the BB-BC. To recapitulate, using the BB-BC algorithm is key to optimise three important aspects of the proposed framework. First, minimise the number of rules contained in the rule base. Second, minimise the number of antecedents at a rule level. Third, optimise the footprint of uncertainty across all fuzzy sets. This addresses one of the shortcomings of the enhanced version presented in the previous chapter. This is the empirical adjustment of the FOU. As a result, this final version is a robust and scalable solution to support target-oriented decision making.

To measure the performance of the optimised BB-BC type-2 FLS, a long short-term memory unit of a recurrent neural network was employed. This new player allowed to have a reference point on the commonly accepted high-performance techniques. However, it also demonstrated that explainability is a limited feature of these black-box approaches. This showcased that these black-box models are not suitable for regulated industries, which require additional detail and insight into operational performance.

Overall, the achieved BB-BC T2 FLS for GDS has been formalised in a structural framework capable to model end-to-end processes in the field service operations domain. The level of detail that can be achieved regarding its underlying model composition is greater compared to other approaches. Moreover, the proposed model presents a novel approach by leveraging traditional simulation to support GDS. This decomposes complexity and brings together expert and non-expert users along with modellers, planers and stakeholders.

The following chapter presents the conclusions of the work presented in this thesis and outlines future work and possible courses of action.

Chapter 10 - Conclusions and Future Work

This thesis has detailed the construction of an intelligent solution for GDS to support field service delivery operations. This proposed solution is a comprehensive framework capable of supporting the achievement of specific targets in simulation environments, benefiting decision making due to the focus on "how-to?" scenarios analysis. This model, and its implementation, aim to avoid repetitive trial and error operations in the simulation of field service operations. The achievements, benefits and future work are detailed in the following subsections.

10.1 Summary of achievements

The aims of the thesis were listed in Chapter 1; a review of the achievements of this thesis in relation to the research objectives can be summarised as follows:

– *To explore the potential for innovative tools for the optimisation of field service delivery*. This goal was achieved by investigating the suitability of fuzzy logic and neural networks to generate concrete results in the GDS context. The methods investigated included type-1 fuzzy logic systems, type-2 fuzzy logic systems, the Big Bang-Big Crunch algorithm, shallow artificial neural networks and short-term memory recurrent neural networks. While better performance was obtained from the deep learning models, better explainability and scalability was obtained from the GDS approach prosed in this work.

– *To include risk-based simulation for sustainable field operations.* This goal was achieved by capturing the risk inherent in the input and output attributes of the model, using interval type-2 fuzzy logic capabilities to model uncertainties based on the footprint of uncertainty.
– *To create a framework for modelling real-world uncertainties.* Although a series of regulation and data compliance measures were put in place, given the real-world aspect of the data used, this goal was achieved by using a synthetic data generation that follows the distribution of real-world uncertainties inherent in the data. The GDS model offers a well-suited data model process, which was detailed in Chapter 6.
– *To enable attainment of specific business targets within reasonable response times and accurate approximations.* This goal was achieved by implementing a "how-to?" scenario analysis approach. Where the classical "what-if?" approach was encapsulated and automated to generate a set of simulated scenarios which were fed into the system. This step reduces effectively the time spent by planners to create their business cases for future service delivery.
– *To disclose relevant accountability elements for the benefit of managers, planners and decision-makers.* This goal was achieved by revealing to users the reasoning behind the GDS model. Contrary to other black-box approaches, the user can access a series of information, such as parameters

that the system uses, rules that intervene in a decision and exploration of the characteristic of the data to enable spotting hidden patterns.

- *To predict service level performance metrics. In daily operations, service performance metrics such as appointment on arrival, appointed resources, completed on the first attempt, attrition rate, productivity, percentage of repair and completed on time are manually inputted by operational planners.* This goal was achieved by creating a detailed data model, which, in turn, allows to create a master metrics/attributes object per each scenario. Hence, the simulation scenario definition as the possibility resulting from a specific set of conditions and configurations. Those conditions and configuration are summarised in the metrics, and it is available for exposure.
- *To exploit machine learning algorithms to predict these measures and propose an optimised plan for operational use. Therefore, the development of novel computational intelligence techniques will support predicting and simulating the risk of resourcing decisions on the business.* Before this proposal, there was a gap between integral solutions and isolated monolithic approaches. Therefore, this was achieved by combining computational intelligence techniques in a harmonised approach, based on Agile Modelling, where the principal focus is the model, along with its aims and capabilities.
- *To enable telecommunication service providers to de-risk investment decisions on the field force and improve operational performance.* The GDS model provides specific values to be changed in the parameters; related to travel time, type of provision and repair tasks, including

appointments, non-appointment, among other attributes that could suffer the variation between the expected and the actual outcome due to uncertainty. Therefore, the proposed solution model allows maximising the effect when the variation is positive since it can result in opportunities. Additionally, the model allows minimising the impact of possible threats since it can help to identify them.

10.2 Contributions

– An end-to-end framework that outlines a series of incremental design, modelling and implementation principles, enabling a dynamic data-driven membership function estimation and generation based on the computation of characteristics for the provided data.
– A structured framework that demonstrates performance improvement by employing fuzzy membership correlation analysis while revelling every step of the proposed solution. As a result, enhanced interpretability is achieved.
– A demonstrated method to evaluate the relevant inputs based on fuzzy theory. The benefits of this include improved performance for GDS models and optimised rule-base based on concise criteria and shorter length of rules that reflect the relevant parameters towards the accomplishment of desired targets.

– A consistent optimisation harmonisation with BB-BC optimisation algorithm as the core to enable operational sustainability in the telecommunications service provider industry.

- A modelling technique that can scale real-life problems while obtaining consistent results when comparing with traditional universal approximators, such as shallow artificial neural networks.
- A concise interpretability capability kept while uncertainty is embedded in the model. The proposed system allowed conditions evaluation for achieving specific business targets before being implemented in real-life conditions, which, in turn, enables the field force operational sustainability nature of this research problem.
- A meticulous incremental framework for implementing "how-to?" scenarios, considering "what-if?" scenarios into the model loop. This approach takes away extra operational cost to users and provides an inherent benefit for planning future scenarios and task-resource allocation.
- A robust simulation environment that builds interpretability while moving from conventional simulation to a target-oriented model. As detailed in Section 9.5, this tool is capable of modelling a reduction between 3.78% and 5.36% of footprint carbon emission due to travel times for jobs completion on customer premises for specific geographical areas. In practice, this translates to a reduction of 135 metric tonnes of carbon emissions for the selected domains. This is aligned with the institutional target of reducing our carbon emission from supply chain operations by 29% by 2030. Currently, the global corporation progress is 8% [213].
- The proposed framework allows generating simulation scenarios 13 times faster than conventional approaches. As detailed in Section 9.6, this contributes to increased productivity and customer satisfaction metrics

referring to keeping to appointment times, completing orders in the promised timeframe or fixing faults when agreed by an estimated 2.6% [147].

– As detailed in Section 9.7, the proposed tool allows evaluating decisions before acting, contributing to the 'promoters' minus 'detractors' across business units measure by an estimated 1% [147].

– Current solutions that address target-oriented problems do not incorporate explainable methodologies, e.g., [3], [4], and [2]; limiting their applicability in highly regulated industries. Moreover, these tools do not provide a mechanism for scalability; therefore, analysis of complex models is limited. Additionally, the lack of an end-to-end methodology to handle uncertainty reduces the applications to linear solutions. The work presented in this thesis mitigates these shortcomings by enabling a concise incremental GDS framework.

– Recently, a framework was developed to understand the performance across a wide range of inputs, namely, the What-If Tool [233]. This tool allows investigating what-if hypothesis by employing visual analytics and multi-class classifications and is capable of adding a layer of explainability to machine learning models. However, there is a lack of end-to-end structure from data generation, model applicability, uncertainty handling and business target definition. Hence, the need for an integrated framework capable of generating "how-to?" scenario analysis that enables structured end-to-end GDS.

– A model that incorporates sustainability concerns such as footprint carbon emissions is essential in the current global emergency, enabling the reduction of greenhouse emission. The work presented in this thesis is relevant because it allows to model emissions generated on the road. For example, according to the European Environment Agency (EEA), 71.7% of the greenhouse gas emissions are generated by road transport [214]. Figure 10.1 illustrates this proportion. Hence, this model is a humble contribution toward providing intelligent tools that facilitate meeting the emission reductions.

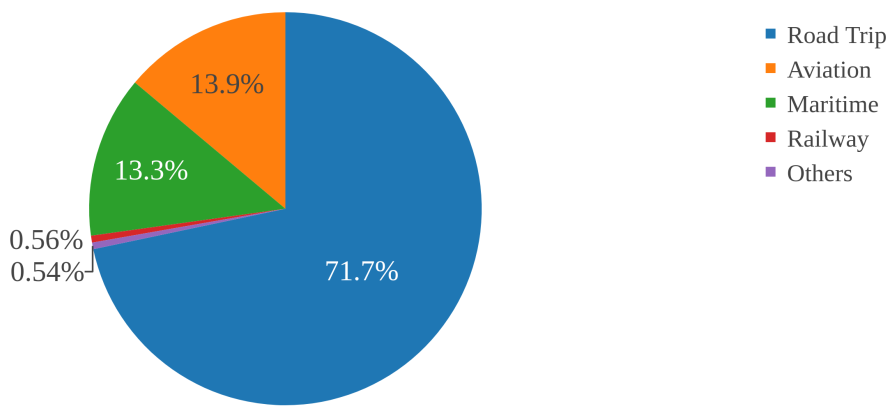

Figure 10.1. Share of transport greenhouse gas emissions (Source: [214])

10.3 Future work

Future work could consider a modification to the architecture to allow parallel BB-BC T2FLS aiming to improve accuracy and keeping the demonstrated benefit for depicting the decision-making process. Furthermore, due to the complexity in the field service simulation domain, future efforts could involve the incorporation of additional simulation capabilities. For example, end-of-the-day simulations inject small perturbations to the model during execution, allowing disruption simulation such as unanticipated strikes, natural disasters or pandemics.

Additionally, a great achievement was to provide the minimum set of inputs in order to achieve the desired targets. Consequently, future work could include the exploration of returning a feasible range for each parameter rather than one value for each parameter, allowing operational planners to forecast better their business cases and to add more room for further modification. Specifically, when events, commonly known as “last minute changes”, occur. Certainly, this is possible since fuzzy logic allows us to model with a range of values instead of fixed crisp ones.

Lastly, future work could explore the implementation of short-term memory recurrent neural network with fuzzy logic. Therefore, the benefits of the model architecture presented in this work might benefit from the performance derived from this specific deep learning models.

10.4 Final thoughts

An opportunity for improvement of this proposal is its domain dependant nature applicable and tested for GDS problems in the field service operation domain, rather than general purpose. However, since robust, reliable XAI systems are generally speaking, in their infancy, it is my hope that the proposed GDS framework, which optimises and reduces its rule base and in parallel handles misclassification cases with a depicted similarity technique, will help to close the gaps between human-understanding and artificial intelligent systems.

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Appendix A — **Overview of Information Sharing Rules**

This section provides a brief overview of the process that BT and Openreach use to manage sensitive Openreach information in line with the Commitments. BT releases periodically the Commitments Implementation report[24], also publicly available in the Ofcom digital library.

In summary, Openreach Commercial Information (CI) or Customer Confidential Information (CCI) cannot be shared with people in BT unless they have a legitimate need to see it and they hold a Regulatory Compliance Marker. This applies where CI/CCI is being sent from Openreach and where it has to be shared between people within BT in order to meet our legal, regulatory or fiduciary duties (e.g., for financial reporting purposes).

A.1. Regulatory Compliance Marker

A Regulatory Compliance Marker is only granted to BT people who have completed the necessary training, provided a satisfactory explanation of why they need a marker, and where it has been approved by both their line manager

24 https://www.btplc.com/Thegroup/Policyandregulation/downloadcentre/2019/BTsProgressReportonCommitmentsImplementation/BTProgressUpdateJune2019.pdf

and a technical authoriser. The technical authoriser confirms they have a legitimate requirement to receive such information in their role.

Where an individual in BT has a relevant marker, they can receive Openreach CI/CCI in one of two ways:

First, routine information (e.g., for developing Openreach's IT systems to support service to their customers and for financial reporting purposes) can be shared under the terms of an Information Sharing Agreement (ISA) between BT and Openreach.

Second, where information legitimately needs to be shared, but it falls outside the scope of any relevant ISA, then it can still be shared provided the sender (in Openreach or BT) completes a disclosure record. The disclosure record is recorded centrally and captures what information is being shared by whom and who it is being shared with.

A report of all information recorded in this way is submitted quarterly to the BTCC and OBARCC. This details the number and type of disclosures being made and draws out common themes making it easier to understand the significance of the information being shared between the two organisations.

Appendix B — Detailed Type-1 Fuzzy Membership Generation

In the context of trapezoidal shapes with two variations left and right shoulders, and triangular the following computes each coordinate for drawing the corresponding shape:

$$S_t = \left\{ \begin{matrix} a\,, \\ \left(1 + sgn\left(-2\,t\; +\; (t\; +\; 1)\right)\right)\, a + sgn(t-1)\, b, \\ sgn\,(T\; -\; t\,)\, c + \left(\,1\; -\; sgn\;\; (t\;\, modulo\;\, T\,)\right) d\,, \\ d \end{matrix} \right\}$$

where $\boldsymbol{S}$ denotes a full set for a $\boldsymbol{t}^{-th}$ linguistic term and $\boldsymbol{sgn}$ represents the sign of a real number. A linguistic term is denoted by $\boldsymbol{t} = \{\mathbf{1}, \mathbf{2}, .., \boldsymbol{T}\}$. $\boldsymbol{T}$ represents the total number of linguistic terms. For the points $\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c}$ and d we apply the following computations, respectively:

$$a = \frac{Mx_p(t-1)}{T} - O$$

$$b = \frac{Mx_p\,(2t-1) - OT}{2T}$$

$$c = \frac{Mx_p\,(2t-1) - OT}{2T}$$

$$d = \frac{Mx_p t}{T}$$

where $\boldsymbol{t} = \{\mathbf{1}, \mathbf{2}, .., \boldsymbol{T}\}$ represents the $\boldsymbol{t}^{-th}$ linguistic term, $\boldsymbol{Mx}$ is the maximum value of the parameter $\boldsymbol{p}$, $\boldsymbol{T}$ is the total of linguistic terms and $\boldsymbol{O}$ is an overlap grade initialised first from a random seed.

Let us assume that the parameter referring to the number of available tasks in the day has a maximum value $\boldsymbol{Mx} = \mathbf{504}$, a total number of linguistic terms $\boldsymbol{T} = \mathbf{7}$ (these are: t = {very very low, very low, low, medium, high, very high, very very high}) and a seeded overlap grade $\boldsymbol{O} = \mathbf{19}$. Therefore, following the computation stated for $\mathbf{S_t}$ at the first element $\boldsymbol{t}$, we have:

For t = 1: { very very low }:

$$S_t = \begin{Bmatrix} a\,, \\ \left(1 + sgn\left(-2(\mathbf{1}) + (\mathbf{1} + 1)\right)\right) a + sgn(\mathbf{1} - 1)\, b, \\ sgn\,(\mathbf{7} - \mathbf{1})\, c + \left(1 - sgn\,(\mathbf{1}\ modulo\ \mathbf{7})\right) d\,, \\ d \end{Bmatrix}$$

By solving the above expression, step by step we obtain:

$$S_t = \begin{Bmatrix} a\,, \\ \left(1 + sgn\left(-\mathbf{2} + (\mathbf{2})\right)\right) a + sgn(0)\, b, \\ sgn\,(\mathbf{6})\, c + \\ \left(1 - sgn\,(\mathbf{1})\right) d\,, \\ d \end{Bmatrix}$$

$$S_t = \begin{Bmatrix} a\,, \\ \left(1 + sgn\,(0)\right) a + (\mathbf{0})\, b, \\ (\mathbf{1})\, c + \left(1 - (+\mathbf{1})\right) d\,, \\ d \end{Bmatrix}$$

$$S_t = \begin{Bmatrix} a\,, \\ (1 + \mathbf{0})\, a + (\mathbf{0})\, b, \\ (\mathbf{1})\, c + (1 - \mathbf{1})\, d\,, \\ d \end{Bmatrix}$$

$$S_t = \left\{ \begin{matrix} a\,, \\ (1)\,a + (0)\,b, \\ (1)\,c + (0)\,d\,, \\ d \end{matrix} \right\}$$

$$\boldsymbol{S_1} = \{\,\boldsymbol{a}\,, \boldsymbol{a}, \boldsymbol{c}\,, \boldsymbol{d}\,\}$$

Now, let us simply substitute the numeric values (Mx_p = 504, T = 7, O = 19 and t = 1) in the corresponding expressions set for a, c and d from the indicated equations as follows:

$$S_t = \left\{ \frac{\mathrm{Mx}_p(\mathrm{t}-1)}{\mathrm{T}} - \mathrm{O}, \quad \frac{\mathrm{Mx}_p(\mathrm{t}-1)}{\mathrm{T}} - \mathrm{O}, \quad \frac{\mathrm{Mx}_p\,(2\mathrm{t}-1) - \mathrm{OT}}{2\mathrm{T}}, \quad \frac{\mathrm{Mx}_p\mathrm{t}}{\mathrm{T}} \right\}$$

$$S_1 = \left\{ \frac{504(1-1)}{7} - 19, \frac{504(1-1)}{7} - 19, \frac{504\,(2\cdot 1 - 1) - 19\cdot 7}{2\cdot 7}, \frac{504\cdot 1}{7} \right\}$$

Solving the arithmetic operations, we obtain:

$$\boldsymbol{S_1} = \{\boldsymbol{-19}, \quad \boldsymbol{-19}, \quad \boldsymbol{26.5}, \quad \boldsymbol{72}\}$$

Similarly, for t = 2: { very low } we have:

$$S_t = \left\{ \begin{matrix} a\,, \\ \big(1 + sgn\,(-2(\mathbf{2}) + (\mathbf{2} + 1))\big)\; a + sgn(\mathbf{2} - 1)\,b, \\ sgn\,(\mathbf{7} - \mathbf{2}\,)\,c + \big(\,1 - sgn\,(\mathbf{2}\;modulo\;\mathbf{7}\,)\big)\,d\,, \\ d \end{matrix} \right\}$$

By solving the above expression, step-by-step we obtain:

$$S_t = \left\{ \begin{matrix} a\,, \\ \big(1 + sgn\,(\mathbf{-4} + (\mathbf{3}))\big)\; a + sgn(\mathbf{1})\,b, \\ sgn\,(\,\mathbf{5}\,)\,c + \big(\,1 - sgn\,(\mathbf{2})\big)\,d\,, \\ d \end{matrix} \right\}$$

$$S_t = \begin{Bmatrix} a\,, \\ \left(1 + sgn\,(-\mathbf{1})\right) a + (+\mathbf{1})\, b, \\ (+\mathbf{1}\,)\, c + \left(\, 1 \;-\; (+\mathbf{1})\right) d\,, \\ d \end{Bmatrix}$$

$$S_t = \begin{Bmatrix} a\,, \\ (\,1 - \mathbf{1})\, a + (\mathbf{1})\, b, \\ (\mathbf{1}\,)\, c + \left(\, 1 \;- \mathbf{1}\right) d\,, \\ d \end{Bmatrix}$$

$$S_t = \begin{Bmatrix} a\,, \\ (\,0)\, a + (1)\, b, \\ (1\,)\, c + \,(\,0)\, d\,, \\ d \end{Bmatrix}$$

$$\boldsymbol{S}_2 = \{\, \boldsymbol{a}\,, \boldsymbol{b}, \boldsymbol{c}\,, \boldsymbol{d}\,\}$$

Now, let us simply substitute the numeric values (Mx_p = 504, T = 7, O = 19 and t = 2) in the corresponding expressions of a, b, c and d from the indicated equations as follows:

$$\mathrm{S_t} = \left\{\frac{\mathrm{Mx_p(t-1)}}{\mathrm{T}} - \mathrm{O}, \frac{\mathrm{Mx_p\,(2t-1) - OT}}{\mathrm{2T}}, \frac{\mathrm{Mx_p\,(2t-1) - OT}}{\mathrm{2T}}, \frac{\mathrm{Mx_p t}}{\mathrm{T}}\right\}$$

$$\mathrm{S_2} = \left\{\frac{504(2-1)}{7} - 19, \frac{504\,(2\cdot 2-1) - 19\cdot 7}{2\cdot 7}, \frac{504\,(2\cdot 2-1) - 19\cdot 7}{2\cdot 7}, \frac{504\cdot 2}{7}\right\}$$

Solving the arithmetic operations, we obtain:

$$\boldsymbol{S}_2 = \{\mathbf{53}, \qquad \mathbf{98.5}, \qquad \mathbf{98.5}, \qquad \mathbf{144}\}$$

Similarly, For t = 3: { low } we have:

$$S_t = \begin{Bmatrix} a\,, \\ \left(\,1 + sgn\left(-2(\mathbf{3}) + \,(\mathbf{3}\; + \;1)\right)\right) a + sgn(\mathbf{3} - 1)\, b, \\ sgn\,(\,\mathbf{7} \;-\; \mathbf{3}\,)\, c + \left(\,1 \;-\; sgn\;\,(\mathbf{3}\;\, modulo\;\, \mathbf{7}\,)\right) d\,, \\ d \end{Bmatrix}$$

Solving the above expression, we obtain:

$$\boldsymbol{S_3} = \{\boldsymbol{a}\,, \boldsymbol{b}, \boldsymbol{c}\,, \boldsymbol{d}\,\}$$

Now, let us simply substitute the numeric values (Mx_p = 504, T = 7, O = 19 and t = 3) in the corresponding expressions of a, b, c and d from the indicated equations as follows:

$$S_t = \left\{\frac{\mathrm{Mx_p}(t-1)}{T} - O, \frac{\mathrm{Mx_p}\,(2t-1) - OT}{2T}, \frac{\mathrm{Mx_p}\,(2t-1) - GL}{2T}, \frac{\mathrm{Mx_p}t}{T}\right\}$$

$$S_3 = \left\{\frac{504(3-1)}{7} - 19, \frac{504\,(2\cdot 3-1) - 19\cdot 7}{2\cdot 7}, \frac{504\,(2\cdot 3-1) - 19\cdot 7}{2\cdot 7}, \right.$$
$$\left. \frac{504\cdot 3}{7}\right\}$$

Solving the arithmetic operations, we obtain:

$$\boldsymbol{S_3} = \{\mathbf{125}, \quad \mathbf{170.5}, \quad \mathbf{170.5}, \quad \mathbf{216}\}$$

This process is completed for all the values in $t = \{1,2,..,T\}$, therefore, for simplicity purposes and following the same process described above we have the following resulting values:

For t = 4: { medium } we have:

$$S_t = \left\{\begin{matrix} a\,, \\ \left(1 + sgn\left(-2(\mathbf{4}) + (\mathbf{4}\ +\ 1)\right)\right) a + sgn(\mathbf{4}-1)\, b, \\ sgn\,(\mathbf{7}\ -\ \mathbf{4}\,)\, c + \left(\ 1\ -\ sgn\ (\mathbf{4}\ modulo\ \mathbf{7}\,)\right) d\,, \\ d \end{matrix}\right\}$$

Solving the above expression, we obtain:

$$\boldsymbol{S_4} = \{\boldsymbol{a}\,, \boldsymbol{b}, \boldsymbol{c}\,, \boldsymbol{d}\,\}$$

Now, let us simply substitute the numeric values (Mx_p = 504, T = 7, O = 19 and t = 4) in the corresponding expressions of a, b, c and d from the indicated equations:

$$S_t = \left\{ \frac{Mx_p(t-1)}{T} - G, \qquad \frac{Mx_p\,(2t-1) - GL}{2T}, \qquad \frac{Mx_p\,(2t-1) - GL}{2T}, \qquad \frac{Mx_p t}{T} \right\}$$

Solving the arithmetic operations, we have:

$$\boldsymbol{S_4} = \{\mathbf{197}, \qquad \mathbf{242.5}, \qquad \mathbf{242.5}, \qquad \mathbf{288}\}$$

For t = 5: { high } we have:

$$S_t = \left\{ \begin{matrix} a\,, \\ \left(1 + sgn\left(-2(\mathbf{5}) + (\mathbf{5} + 1)\right)\right) a + sgn(\mathbf{5} - 1)\, b, \\ sgn\,(\mathbf{7} - \mathbf{5})\, c + \left(1 - sgn\,(\mathbf{5}\ modulo\ \mathbf{7})\right) d\,, \\ d \end{matrix} \right\}$$

Solving the above expression, we obtain:

$$\boldsymbol{S_5} = \{\boldsymbol{a}\,, \boldsymbol{b}, \boldsymbol{c}\,, \boldsymbol{d}\}$$

Now, let us simply substitute the numeric values (Mx_p = 504, T = 7, O = 19 and t = 5) and solve the arithmetic operations for $\boldsymbol{a}$, $\boldsymbol{b}$, $\boldsymbol{c}$, and $\boldsymbol{d}$. As a result, we have:

$$\boldsymbol{S_5} = \{\mathbf{269}, \qquad \mathbf{314.5}, \qquad \mathbf{314.5}, \qquad \mathbf{360}\}$$

For t = 6: { very high } we have:

$$S_t = \left\{ \begin{matrix} a\,, \\ \left(1 + sgn\left(-2(\mathbf{6}) + (\mathbf{6} + 1)\right)\right) a + sgn(\mathbf{6} - 1)\, b, \\ sgn\,(\mathbf{7} - \mathbf{6})\, c + \left(1 - sgn\,(\mathbf{6}\ modulo\ \mathbf{7})\right) d\,, \\ d \end{matrix} \right\}$$

Solving the above expression, we obtain:

$$\boldsymbol{S_6} = \{\boldsymbol{a}\,, \boldsymbol{b}, \boldsymbol{c}\,, \boldsymbol{d}\,\}$$

Now, let us simply substitute the numeric values (Mx_p = 504, T = 7, O = 19 and t = 6) and solve the arithmetic operations for $\boldsymbol{a}$, $\boldsymbol{b}$, $\boldsymbol{c}$, and $\boldsymbol{d}$. As a result, we have:

$$\boldsymbol{S_6} = \{\mathbf{341}, \quad \mathbf{386.5}, \quad \mathbf{386.5}, \quad \mathbf{432}\}$$

For t = 7: { very very high } we have:

$$S_t = \left\{ \begin{matrix} a\,, \\ \left(1 + sgn\left(-2(\mathbf{7}) + (\mathbf{7} + 1)\right)\right) a + sgn(\mathbf{7} - 1)\, b, \\ sgn\,(\mathbf{7} - \mathbf{7})\, c + \left(1 - sgn\ (\mathbf{7}\ modulo\ \mathbf{7})\right) d\,, \\ d \end{matrix} \right\}$$

Solving the above expression, we obtain:

$$\boldsymbol{S_7} = \{\boldsymbol{a}\,, \boldsymbol{b}, \boldsymbol{d}, \boldsymbol{d}\,\}$$

Now, let us simply substitute the numeric values (Mx_p = 504, T = 7, O = 19 and t = 7) and solve the arithmetic operations for a, b and d. As a result, we have:

$$\boldsymbol{S_7} = \{\mathbf{413}, \quad \mathbf{458.5}, \quad \mathbf{504}, \quad \mathbf{504}\}$$

Finally, every obtained value $\boldsymbol{S_1}, \boldsymbol{S_2}, \boldsymbol{S_3}, \boldsymbol{S_4}, \boldsymbol{S_5}, \boldsymbol{S_6}$ and $\boldsymbol{S_7}$ is plotted as the theoretical union of all subsets. Figure 7.3 illustrates the resulting plot.

Appendix C — **RMSE Results for Large Scale Experiments**

This section provides detailed comparison among different systems trained and tested in the final iteration of the proposed framework. Each table corresponds to a particular geographic area. The analysis of these results can be reviewed in Section 9.4.5.

Table C.1– RMSE comparison among different systems in the training phase for geographic **AT**.

Goal	**Training**			
	Type-1	**BB-BC T2FLS**	**ANN**	**LSTM RNN**
1	0.8522452	0.5968733	0.3405876	0.3471691
2	0.5730032	0.2849943	0.2370167	0.2562298
3	0.7277007	0.4111857	0.2911455	0.2895607
4	0.3524441	0.1601039	0.1502808	0.1703846
5	0.9945181	0.9309289	0.5857034	0.5905171
6	0.9370781	0.9638549	0.6535476	0.6649232
Average	**0.739498233**	**0.557990167**	**0.376380267**	**0.38646408**

Table C.2– RMSE comparison among different systems in the testing phase for geographic **AT**.

Goal	Testing			
	Type-1	BB-BC T2FLS	ANN	LSTM RNN
1	0.7928875	0.6327269	0.3090516	0.3234958
2	0.5715524	0.2962385	0.2324312	0.2570131
3	0.6043349	0.4329598	0.2347248	0.2440939
4	0.3183252	0.25783219	0.0961514	0.1179203
5	0.9597750	0.91988963	0.5586890	0.5762399
6	0.9114777	0.89775813	0.6256429	0.2440939
Average	**0.693058783**	**0.572900858**	**0.342781817**	**0.293809483**

Table C.3– RMSE comparison among different systems in the training phase for geographic **EB**.

Goal	Training			
	Type-1	BB-BC T2FLS	ANN	LSTM RNN
1	0.86076765	0.60881077	0.34399348	0.35515399
2	0.57873323	0.29069419	0.23938687	0.26212309
3	0.73497771	0.41940941	0.29405696	0.2962206
4	0.35596854	0.16330598	0.15178361	0.17430345
5	1.00446328	0.94954748	0.59156043	0.60409899
6	0.94644888	0.983132	0.66008308	0.68021643
Average	**0.74689322**	**0.56914997**	**0.38014407**	**0.39535276**

Table C.4– RMSE comparison among different systems in the testing phase for geographic **EB**.

Goal	Testing			
	Type-1	BB-BC T2FLS	ANN	LSTM RNN
1	0.80081638	0.64538144	0.31214212	0.3309362
2	0.57726792	0.30216327	0.23475551	0.2629244
3	0.61037825	0.441619	0.23707205	0.24970806
4	0.32150845	0.26298883	0.09711291	0.12063247
5	0.96937275	0.93828742	0.56427589	0.58949342
6	0.92059248	0.91571329	0.63189933	0.24970806
Average	**0.69998937**	**0.58435888**	**0.34620963**	**0.3005671**

Table C.5– RMSE comparison among different systems in the training phase for geographic **CD**.

Goal	Training			
	Type-1	BB-BC T2FLS	ANN	LSTM RNN
1	0.87781256	0.61179513	0.34433406	0.35567474
2	0.5901933	0.29211916	0.23962388	0.26250743
3	0.74953172	0.42146534	0.2943481	0.29665494
4	0.36301742	0.1641065	0.15193389	0.17455902
5	1.02435364	0.95420212	0.59214614	0.60498477
6	0.96519044	0.98795127	0.66073662	0.68121382
Average	**0.76168318**	**0.57193992**	**0.38052045**	**0.39593245**

Table C.6– RMSE comparison among different systems in the testing phase for geographic **CD**.

Goal	Testing			
	Type-1	**BB-BC T2FLS**	**ANN**	**LSTM RNN**
1	0.81667413	0.64854507	0.31245117	0.33142145
2	0.58869897	0.30364446	0.23498794	0.26330992
3	0.62246495	0.4437838	0.23730677	0.2500742
4	0.32787496	0.26427799	0.09720907	0.12080935
5	0.98856825	0.94288687	0.56483458	0.59035778
6	0.93882203	0.92020208	0.63252497	0.2500742
Average	**0.71385055**	**0.58722338**	**0.34655242**	**0.30100782**

Table C.7– RMSE comparison among different systems in the training phase for geographic **WU**.

Goal	Training			
	Type-1	**BB-BC T2FLS**	**ANN**	**LSTM RNN**
1	0.86502888	0.80577896	0.34739935	0.357237
2	0.58159825	0.38474231	0.24175703	0.26366046
3	0.73861621	0.5551007	0.29696841	0.29795796
4	0.35773076	0.21614027	0.15328642	0.17532575
5	1.00943587	1.25675402	0.59741747	0.6076421
6	0.95113427	1.30120412	0.66661855	0.68420597
Average	**0.75059071**	**0.75328673**	**0.38390787**	**0.39767154**

Table C.8– RMSE comparison among different systems in the testing phase for geographic **WU**.

Goal	Testing			
	Type-1	**BB-BC T2FLS**	**ANN**	**LSTM RNN**
1	0.80478081	0.85418132	0.31523263	0.33287718
2	0.58012569	0.39992198	0.23707982	0.26446648
3	0.61339992	0.58449573	0.2394193	0.25117262
4	0.32310008	0.34807346	0.09807443	0.12133999
5	0.97417163	1.241851	0.56986278	0.59295086
6	0.92514987	1.21197348	0.63815576	0.25117262
Average	**0.70345467**	**0.77341616**	**0.34963745**	**0.30232996**

Table C.9– RMSE comparison among different systems in the training phase for geographic **AD**.

Goal	Training			
	Type-1	**BB-BC T2FLS**	**ANN**	**LSTM RNN**
1	0.8692901	0.61418263	0.34739935	0.35411248
2	0.58446326	0.29325913	0.24175703	0.2613544
3	0.74225471	0.42311009	0.29696841	0.29535191
4	0.35949298	0.16474691	0.15328642	0.17379229
5	1.01440846	0.95792584	0.59741747	0.60232744
6	0.95581966	0.99180669	0.66661855	0.67822166
Average	**0.7542882**	**0.57417188**	**0.38390787**	**0.39419337**

Table C.10– RMSE comparison among different systems in the testing phase for geographic **AD**.

Goal	Testing			
	Type-1	BB-BC T2FLS	ANN	LSTM RNN
1	0.80874525	0.65107598	0.31523263	0.32996572
2	0.58298345	0.30482942	0.23707982	0.26215336
3	0.6164216	0.44551563	0.2394193	0.24897578
4	0.3246917	0.26530932	0.09807443	0.12027871
5	0.9789705	0.94656643	0.56986278	0.5877647
6	0.92970725	0.92379312	0.63815576	0.24897578
Average	**0.70691996**	**0.58951498**	**0.34963745**	**0.29968567**

Table C.11– RMSE comparison among different systems in the training phase for geographic **WN**.

Goal	Training			
	Type-1	BB-BC T2FLS	ANN	LSTM RNN
1	0.86758561	0.60702015	0.34569641	0.35688983
2	0.58331726	0.2898392	0.24057195	0.26340423
3	0.74079931	0.41817586	0.29551268	0.2976684
4	0.35878809	0.16282567	0.15253501	0.17515537
5	1.01241943	0.94675469	0.59448895	0.60705158
6	0.95394551	0.98024043	0.66335081	0.68354105
Average	**0.7528092**	**0.567476**	**0.38202597**	**0.39728508**

Table C.12– RMSE comparison among different systems in the testing phase for geographic **WN**.

Goal	Testing			
	Type-1	BB-BC T2FLS	ANN	LSTM RNN
1	0.80715948	0.64348326	0.31368737	0.33255368
2	0.58184034	0.30127455	0.23591767	0.26420947
3	0.61521293	0.44032012	0.23824567	0.25092853
4	0.32405505	0.26221534	0.09759367	0.12122207
5	0.97705095	0.93552775	0.56706934	0.59237462
6	0.9278843	0.91302002	0.63502754	0.25092853
Average	**0.70553384**	**0.58264017**	**0.34792354**	**0.30203615**

Table C.13– RMSE comparison among different systems in the training phase for geographic **LC**.

Goal	Training			
	Type-1	BB-BC T2FLS	ANN	LSTM RNN
1	0.86843786	0.60881077	0.34399348	0.35758417
2	0.58389026	0.29069419	0.23938687	0.26391669
3	0.74152701	0.41940941	0.29405696	0.29824752
4	0.35914054	0.16330598	0.15178361	0.17549614
5	1.01341394	0.94954748	0.59156043	0.60823261
6	0.95488258	0.983132	0.66008308	0.6848709
Average	**0.7535487**	**0.56914997**	**0.38014407**	**0.39805801**

Table C.14– RMSE comparison among different systems in the testing phase for geographic **LC**.

Goal	Testing			
	Type-1	**BB-BC T2FLS**	**ANN**	**LSTM RNN**
1	0.80795236	0.64538144	0.31214212	0.33320067
2	0.5824119	0.30216327	0.23475551	0.26472349
3	0.61581726	0.441619	0.23707205	0.25141672
4	0.32437338	0.26298883	0.09711291	0.12145791
5	0.97801073	0.93828742	0.56427589	0.5935271
6	0.92879578	0.91571329	0.63189933	0.25141672
Average	**0.7062269**	**0.58435888**	**0.34620963**	**0.30262377**