Exploiting Lion Optimization Algorithm for Sustainable Energy Management System in Industrial Applications

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Abstract

Energy is the soul of each new invention on this Bio-sphere. The upturn in this advancement and technological growth, energy resources are getting scarce. As the energy resources are limited and can not be increased in the same proportion as with the exponential rising demand, that is why, we have to manage our energy consumption smartly. An optimal integration of the Renewable energy sources (RESs) for this purpose is the need of the day. This paper proposes a bio-inspired algorithm, namely, the Lion's Algorithm (LA), for an efficient Energy Management System (EMS) in industrial areas, along with a beneficial utilization of RES and energy storing units (ESUs). Different objectives, like, Total Energy Cost (TEC), Peak to Average power Ratio (PAR), Hourly Load (HL) and maximization of end-user comfort (the reduction in waiting time) are analyzed and observed. LA algorithm is specially designed to achieve these objectives up-to maximum optimal limits. The MATLAB simulation results illustrate that, our proposed algorithm reduced the cost upto 42.66% and PAR

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35.94% compared to un-scheduled and scheduled with other state-of-the-art algorithms, with an average waiting time of only 0.216 hrs (12.96 sec).

Keywords: Bio-inspired Algorithms, Energy Management System, Energy Optimization, Lion Algorithm, Smart Grid, Traditional Electric Power Grid, Sustainable Energy

1. Introduction

Scientific research sparked the industrial revolution, ushering in a new era of improvement in every facet of existence. Through the use of new equipment and amenities made possible by modern technologies, human existence has become more comfortable [1], [2]. The universe's latent potentials are being explored through new science. All of these explorations and advancements are possible because of electricity. All mechanical and electrical mechanisms have been converted to run on energy sources as a result of industrial advancement, increasing their demand and resulting in energy shortfall over the last few decades. This is a critical time to increase the efficiency and effectiveness of these resources in order to conserve energy. Although researchers in the electrical domain have devised numerous processes and mechanisms, one such mechanism is the application of optimization techniques. Advanced infrastructure is critical for economic progress, which takes yet another massive amount of energy. However, the amount of energy that is accessible remains constant because installed power plants generate a finite amount of energy. Increased energy production or the construction of new power plants is an expensive and time-consuming operation that developing countries cannot afford. Researchers have used a variety of strategies and technologies in order to address these issues. These strategies make use of algorithms inspired by nature, bio-inspired algorithms, and mathematical models. To identify the optimal solution, researchers model complex problems using various optimization algorithms.

Electrical energy's invention ushered in a period of profound change in human history. It has numerous benefits for human life, ranging from everyday use such as lighting, washing clothes, and cooling systems (refrigeration or air-conditioning) to communication systems and industrial level. The world's future will be entirely reliant on electrical potential, but there is a problem here: energy scarcity. As a result, we employ an optimization process to maximise the efficiency of existing resources, which has been made possible by the advancement of Smart Grid (SG) technology. Due to the advantages of power exchange and communication between consumers and utilities, proper power management occurs, resulting in benefits such as reduced peak to average power ratio (PAR), reduced electricity bills, and similarly decreased frequency of system interruptions, resulting in increased system reliability and sustainability.

Various algorithms, such as the Particle Swarm Optimization (PSO) algorithm, the Multi-verse Optimization (MVO), the Dragonfly algorithm, and the Wind-driven optimization algorithms, have all been used to provide comfort using the optimization concept. The Lion's Algorithm (LA) is proposed in this paper to achieve not only the above objectives, but also the optimal integration of consumer-generated energy resources like solar and wind turbines.

Demand-Side Management (DSM) is concerned with the load on consumers. It serves two primary functions: load management and demand response (DR) [3]. Every energy-consuming area is equipped with Smart Meters SM and AOAs. In EMC, smart metre communication is primarily used to transmit pricing signals and monitor power consumption. Consumers are kept informed about their consumption through bidirectional communication in SM and unidirectional power flow. Keeping peak hours in mind, the Energy Management Controller (EMC) is responsible for scheduling the appliances. Each appliance should complete its assigned time slot in order to achieve its optimization objective [4, 5]. Given that energy is produced in a fixed quantity, its supply will almost certainly be directly proportional. That is why we require appropriate techniques and methods for efficiently utilising energy in order to maintain the production supply chain [6]. Traditional grids are incapable of meeting this energy demand, which is why smart grids (SG) have been proposed and implemented in certain areas. The smart grid (SG) improves the resilience and consistency of existing power grids. A critical component of SG is the smart metre (SM), which is used not only for bidirectional communication but also for energy monitoring. In SG, the EMC is responsible of scheduling appliances in the residential, commercial, and industrial sectors. EMC works in conjunction with Automated Appliances (AOAs) and a sophisticated communication and distribution system. SM, in collaboration with EMC, schedules the appliances based on the utility's pricing signal and data on the length of the machines' operational time [7].

We conducted various simulations to demonstrate that our proposed algorithm intelligently minimised energy costs, PAR, and machine waiting time. To accomplish this, a smart grid for industrial load management is implemented and modelled for various LOTs and machine power ratings. Different machines in the industry have varying power ratings, owing to their varying dimensions and application in varying load units. Thus, in order to manage such a system, we require an algorithm capable of producing satisfactory results.

Similarly, if the energy provider provides an incentive to its customers in the form of real-time low prices during non-peak hours, this would be extremely beneficial. The remaining paper is structured as follows. Section 3 discusses related work. Section 4 discusses briefly the model architecture and the analysis of real-time data. Section 5 contains a description of our proposed Lion's Algorithm (LA). Section 6 compares the simulation results for the Pricing Signal, Daily Average Load, Hourly Load, Hourly electricity cost, PAR, Total Cost, and waiting time to several state-of-the-art optimization algorithms. The final section of the paper contains the conclusion.

2. Background and Related Work

Numerous researches, all over the world, have proposed different optimization techniques. In [8], the authors have proposed a mixed-integer linear programming approach for finding a way to balance the load and adjustment of cost in more populated areas. However, they didn't consider user comfort, which is the main focus of current research. In [9, 10], authors have used three different meta-heuristic techniques, i.e., the Harmony Search Algorithm (HSA), Enhanced Differential Evolution (EDE) and the Bacterial Foraging Algorithm (BFA),for optimal utilization of the existing energy facilities. The result analysis reveals that HSA is the best in terms of cost as compare to BFA and EDE. Although, HAS reduced the electricity cost more than the other two algorithms, yet the un-scheduling cost of each algorithm is greater. Appliances have been scheduled according to the day ahead pricing (DAP) signal. In pricing signals, crusts and troughs appear according to uses. The algorithm shifts the appliances to less energy cost hours, in which, per unit electricity price is less as compared to on-peak hours. The highest quantity of energy consumed in an unscheduled case is 12.0750 kWh. While after applying the algorithm, the new readings are 9.0152kWh, 9.4750kWh, and 9.7750 kWh in cases of HAS, EDE, and BFA respectively. EDE achieved sound in the case of PAR and BFA in the case of reducing user discomfort.

For attaining good results in terms of cost and PAR minimization, Genetic Algorithm (GA), Moth-Flame Optimization algorithm (MFO) and a hybrid version of the GA and MFO, namely, Time-constrained Genetic Moth-Flame Optimization (TG-MFO) algorithms are used in [11**?**]. In [12], BFA, GA and a hybrid version of these two algorithms, are used for energy optimization. These algorithms focus mainly on cost and PAR minimization and load management on consumer side. The results show that, the day-bsed energy cost is less in the hybrid algorithm as compared to its parents algorithms, GA and BFA. This approach has saved 10% of unscheduled cost. PAR for BAF is low but the cost figure is high. In the case of the hybrid approach, PAR is less as compared to GA, and the waiting time is also reasonable. In [13], researchers have divided appliances into two categories, one is power flexible and the second one is time flexible to acquire minimum electricity cost and decrease the waiting time. The authors used a hybrid version of Common Scrambling Algorithm (CSA) and Earthworm Optimization Algorithm (EWA) algorithms in [14]. Based on their calculations, they reduced the cost up to 50.6% by RTP signaling.

Similarly, in [15], the author draws a comparison between GA and the CSA for the total cost calculation, waiting time, and PAR reduction. By using GA, the cost is reduced by 22.840%, while, CSA has reduced it 21.470%. GA achieved PAR reduction up-to 3.63 (18.240% reduction) and 3.7198 for CSA (19.0% reduction) concluding that GA is better for cost reduction and CSA for PAR reduction. All results are based on appliances scheduling according to pricing signals. Electricity price is different in different time slots due to which electric companies made their consumers aware to shift appliances from on-peak hours to off-peak hours. In [16, 17, 18], the main grid is connected with the micro-grid to for minimization of both, PAR and energy cost, using the optimization techniques viz GWO, BPSO, GA, and WDO. To get better results, they have used hybrid versions of the different algorithms. The function of the DMS program is to provide support to power in different areas, such as infrastructure maintenance, control of electricity, and providing the best way to manage energy resources [19]. In a large scale, the load is shifted between PHs and OPHs in residential areas. Appliances are divided into two major portions, non-shiftable and shiftable. The proposed hybrid's results are better as compare to other techniques [20, 21, 22]. In [23], the author used a Q-learning algorithm for the optimal DR mechanism. This is a fully automated system for the residential sector. An energy model BPOS is used on behalf of DMS. It aims to control electricity costs in residential areas by scheduling shiftable appliances. For the investigation of the DR mechanism, the Time-Of-Use (ToU) pricing model is used for the manipulation of energy-cost, however, user discomfort due to this scheduling is ignored in [24]. BFOA works on a Hyper-Heuristic Resource Scheduling (HHRS) algorithm for the grid. The operational completion time of the last job to leave the system and cost performance metrics are used to compare BFOA with the existing resource scheduling algorithm which is GA and annealing. Purposed algorithm results show that it performed well in terms of cost minimization [25, 26]. In [27, 21], scholars enhanced the reliability and efficiency in SG to produce minimization of the cost by data-centers and cloud grid infrastructure. The presented DR mechanism minimizes cost, minimizes the UdC and maximizes the privacy in [28]. The authors in [29, 30, 31, 32] give a detailed report on load management strategies. The power transmission of SG, communication between RUs and SG for NANs or HANs are discussed. Dynamic Pricing-Based and Incentive-Based Scheduling Schemes are described to elaborate peak shaving. Finally, the authors give a brief estimate of Load Management techniques and major challenges because of LM in SG.

3. Research Challenges

As mentioned earlier, that, an efficient energy management system is essential due to the un-efficient utilization of existing energy resources in the traditional electric power grids. By exploiting various computational techniques and algorithms, the aforementioned problem could be solved comfortably. Although, researchers have proposed numerous types of bio-inspired algorithms, however, these research works have mostly ignored the end-user discomfort due to scheduling of their appliances in either residential, commercial or industrial sectors, while minimizing their electricity-bills and PAR. That's why, in this research work, we use a new bio-inspired technique for industrial application. In industrial sector, we have divided our load in different load units. The scheduling of appliances is one of the most important requirements to optimize the performance of these different load units. The objectives of scheduling are to reduce; the electricity bill, PAR, aggregated power consumption and appliances waiting time in order to minimize the end-user's discomfort, etc. In this regard, the current research in SG majorly focuses on optimization techniques for power scheduling. As, in the present era of electricity dependent modern technologies, user wants to finish his job quickly, instead of waiting for his appliances to start. On the other hand, the consumption has to be minimized in order to reduce the cost as well. But unfortunately, these research attempts have ignored frequency of interruptions and aggregated power consumption, as these issues threaten reliability, stability, sustainability and security of Smart Grid.

4. Objectives

There are four main objectives of our work as listed below:

1. Minimization of end-users frustration due to scheduling of their machines;
2. Minimization of end-users consumed energy-cost;
3. Minimization of PAR;
4. Integration of RESs.

The mathematical models of our objective functions are given as follow:

$$E_T^N = \sum_{n=1}^{N} W_n \times X_n \tag{1}$$

In the above equation, W_n is the power of n^{th} machine, N shows the total no of machines in a given load unit, X_n is the ON-time in a time slot of n^{th} machines and E_T^N is the total energy calculated for all load units in a single time slot.

Now the total cost C_{Sch} for all scheduled appliances can be calculated by multiplying total energy $E_{T,m}^N$ calculated in m^{th} time slot with the respective energy price ζ_m in that time slot.

$$C_{Sch} = \sum_{m=1}^{M} E_{T,m}^N \times \zeta_m \tag{2}$$

C_{unsch} is the total energy price for all slots of Unscheduled appliances calculated in the similar manner, then the normalized C_{Norm} of scheduled appliances can be calculated as:

$$C_{Norm} = \frac{C_{Sch}}{C_{Sch} + C_{unsch}} \tag{3}$$

Now, let the starting time of a machine is α and the operation finishing time is β, then the new variable η will be the actual operational starting time of that machine. Then, the consumer's maximum waiting time could be up to η_{max}. Therefore, η_{max}, will be the maximum operation starting time, after which the machine must start, so that, the machine will complete its operation up to the final time β.

Now, since,

$$(\beta - \alpha) \geq LOT \tag{4}$$

Therefore, the range of waiting time can be α to η_{max}.

Machines normalized waiting time (τ_w) can be calculated as:

$$\tau_w = \frac{\eta - \alpha}{\eta_{max} - \alpha} \tag{5}$$

Equation (1.5) shows that the normalized waiting time can be from "0" (when $\eta = \alpha$) to "1" (when ($\eta = \eta_{max}$). Now, the final expression for minimization function is given by the following equation:

$$min\left((\lambda_1 \times C_{Norm}) + (\lambda_2 \times \tau_w)\right) \tag{6}$$

Our proposed objective function aims to reduce electricity cost, while maintaining higher end user comfort level by minimization of waiting time. λ_1 and λ_2 are multiplying factors of two portions of our objective function. Their values varies between '0' and '1' so that $\lambda_1 + \lambda_2$=1 . It reveals that either λ_1 and λ_2 could be 0 to 1. That is, if an end user does not want to participate in the load scheduling process, then his multiplying factors will be λ_1 =1 and λ_2 =0 in the objective function.

5. Model Architecture

The EMS in the smart grid consists of two main sides, DMS (Demand Side Management) and SSM (Supply Side Management). Smart Meter (SM) has AMI (Advanced Metering Infrastructure) technology, used for bilateral communication between consumer and supply. Machines have different patterns of EMC.

Energy Management Control (EMC) then adjusts its load relative to the pricing signal received from the company. Figure 1 depicts the proposed system model architecture.

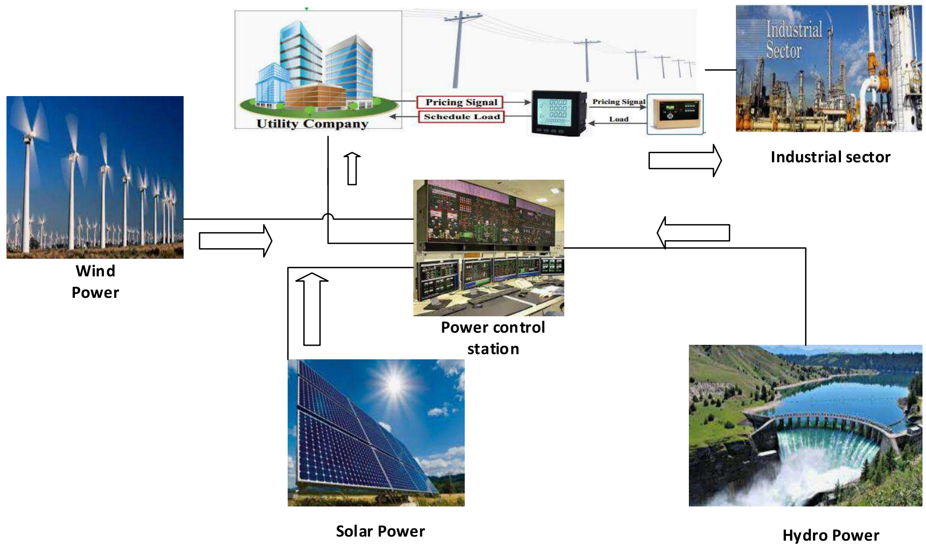

Figure 1: Proposed System Model Architecture

Smart Meter SM collects the pricing signal and direct it to EMC. Meanwhile, it collects a power signals from EMC and forward it to the energy providers (company). This communication can be done through different media, like, Wi-Fi, ZigBee, Global System for Mobile Communication (GSM), etc [33]. In an industry system with different sections carry different load units. We have taken a crushing mill as a case study in this paper. It has different automatic operated machines (AOMs), with different power ratings as depicted in Figure 2.

Mill-A and Mill-B are both of the same categories. They use one of them at a time. This Mill-A/B takes 177KW power and it consists of different types of motors i.e. Main Mill 75KW, Crusher/Compressor 82 KW, and Rotary/Elevator 20KW. These induction motors are 100HP, 110HP, and 26HP respectively. Mill-C takes 299KW and consists of 3 types of motors i.e. 176HP, 150HP, and a

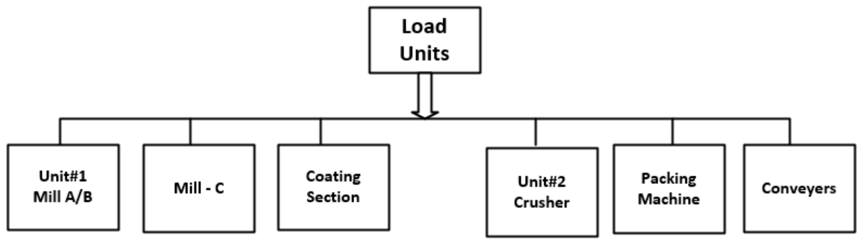

Figure 2: Load Units

slip ring motor of 84HP. The coating section takes the power of 162KW and having two types of induction motors of 148HP and 68HP. The jaw crusher section takes 90KW having two motors 100HP and 20HP. The packing section takes 15KW and has only one type motor of 7HP. Conveyor takes 14.5KW and having one motor of 10HP. The estimated load of the mill is 350KW which indicates that at the same time interval, 4 to 5 motors are in working condition. The Maximum Demand Indicator (MDI) is measured to be 400KW. Keeping demand in mind machines do their work till overload. Table 1 summarizes the load units, power ratings and their length of operational times (LOT).

Table 1: Industrial load units and their power ratings and length of operational times

AOMs	**Power Rating(KW)**	**LOT (Hrs)**
Mill A/B	177kW	8
Mill - C	299kW	5-8
Coating Section	162kW	7
Unit # 2	90kW	10
Packing Machine	15kW	9
Conveyers	14.5kW	12

6. Scheduling Algorithm

The different algorithm has been used in literature to achieve low PAR, low energy cost and user relief for the optimal solution of appliances scheduling time. In this paper, The Lion's Algorithm has been used which is a new Nature-Inspired Search Algorithm. A brief description of this algorithm is given below.

6.1. The Lion's Algorithm (LA)

The lion, regarded as the most powerful animal on the planet, fights not only for its prey but also for the survival of other mammals. The optimal solution provided by the Lion's Algorithm is based on lion behaviours. Because a lion cub matures between 2-4 years, the territorial lion must defend his territory for the same amount of time. Nomadic or roving lions conquer during this time period, which is referred to as territorial or regional defence. The nomadic lions and the regional lions engage in combat. If the nomadic lion gains dominance, it slaughters all of the beaten lion's newborn cubs and forces the female lion to reproduce for the next generation. This nomadic lion will now take on the role of territorial lion. When the pride's cubs reach maturity, they either kill or expel the territorial lion. This invader lion kills and gives birth to the regional lion's cubs.

The inspiration behind this algorithm is to study its social behavior and find an optimal solution for a large-scale solution. The algorithm gives the solution based on both single and multi-variable. Territorial defense and territorial takeover are two behaviors which give optimal solution. Lion is the main solution and cubs give the solution-driven from the lion's solution. Evolution takes place in territorial defense when the existing solution (the territorial lion) is replaced with new solutions (the nomadic lion). If this newly generated solution is better, then the old driven solution is removed.

The aim of the territorial takeover is only to keep the best male lion and the female lion solution and remove all others. Following are the steps involved in The Lion's Algorithm. Based on its nature, it has four major components. These are given as follow;

1. Pride Generation, for new solutions.;
2. Mating, for developing a new solution;
3. Territorial or regional Defense;
4. Territorial takeover to find new best solutions and replacing the old ones.

The process is repeated until the desired solution is obtained. The pride is an energetically varied size solution initially with two solutions. One is for males and the other is for females. Which keeps the driven solutions and removed the lousy solution. The procedure of mating is for generating new solutions from already existing solutions by mutation and crossover. Gender gaping is the difference among the resolutions and killing new born cubs means derived solutions are best.

The search process of the Algorithm follows its basic function. For the optimal solutions, the objective function is.

$$argminf(p_1, p_2 \cdots p_n) n \geq 1 \tag{7}$$

$$p_i(p_i^{min}, p_i^{max}) \tag{8}$$

The above Eq. (7) $n-variable$ minimization function for every solution variable may indicate certain equalities and inequalities. Lion has binary structured when n=1 and integer for $n > 1$. Initial pride is structured as $p^{male} = [p_1^{male}, p_2^{male}, \cdots p_L^{male}]$ and $p^{female} = [p_1^{female}, p_2^{female}, \cdots p_L^{female}]$ where L is solution length vector given as.

$$L = \{ \begin{array}{ll} n & n \geq 1 \\ m & otherwise \end{array} \tag{9}$$

Eq. (9), p_l^{male} and p_l^{female}, where $l = 1, 2 \cdots L$ are integers in (p_l^{min}, p_l^{max}) for $n > 1$. On the other hand, p_l^{male} and p_l^{female} may be either 0 or 1 at $n = 1$ such that $h(p_l) = (p_l^{min}, p_l^{max})$. The $h(p_l)$ is for both p_l^{male} and p_l^{female}

$$h(p_l) = d(p_1) \sum_{l=2}^{L} 2^{L-l} p_1 \tag{10}$$

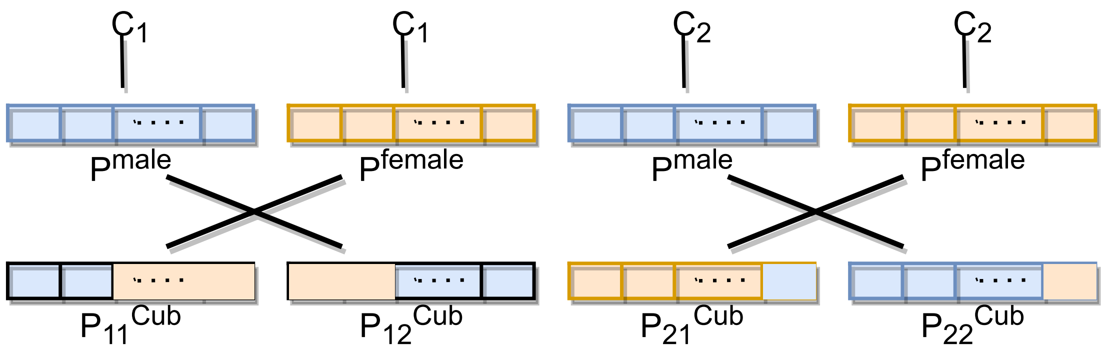

Figure 3: Different probabilities of crossover

where

$$k(p_l) = \begin{cases} 1 & if\, p_1 = 0 \\ -1 & otherwise \end{cases} \tag{11}$$

Through the process of crossover and mutation of p_l^{male} and p_l^{female}, four (4) new p^{cub} are produced. Figure 3 depicts two different probabilities of the crossover. After the generation of p^{cub} from crossover and p^{new} from mutation, the cub pool shows 4 direct cubs and 4 mutated cubs and this is referred to as gender grouping. The clustering process of gender grouping is to derive two solution groups, one for $p^{p^{m-cub}}$ male cubs and others for p^{f-cub} female cubs. For the stability of the cub pool and to update the pride it is considered to be necessary to kill the weak cubs. This killing by testing the health is to keep the male and female cubs equal in number which also determines the objective function worth of every cub. The existing territorial lion gets this stabilized cubs pool and initialized to zero. During every territorial defense success, the cubs' age is incremented by on. Following pseudo-code shows the territorial defense and territorial takeover. In the pseudo-code, by following the process of p^{male} similar is followed for p^{nomod} . Instance objective function is $f(\dot{)}$. p^{male} and p^{nomod} have the objective function values $f(p^{male})$ and $f(p^{nomod})$ and also their strength respectively whereas $f(p^{pride})$ is entire pride strength calculated as.

$$f(p^{pride}) = \frac{1}{2(1+\|p^{m-cub}\|)} \left(f(p^{male}) + f(p^{female}) + \frac{Age_{mat}}{age(cub)+1} \sum_{Z=1}^{\|p^{m-cub}\|} \frac{f(p_Z^{m-cub}) + f(p_Z^{f-cub})}{\|p^{m-cub}\|} \right) \tag{12}$$

Where, $f(p_Z^{m-cubs})$ and $f(p_Z^{f-cubs})$ are the statuses of male cubs and female cubs, $\|p^{m-cub}\|$ denotes the number of male lion cubs in pride where Age_{mat} is the age maturity of cubs.

The coalition property of this algorithm gives a strong solution for pride. It processes the new solution in such that this new solution is better the capability of both the present solution and pride. Once the cubs reach the maturity level Age_{mat}, they are considered lions and started defending with old's line pride to prove their strength.

At the start of the territorial takeover, build p_{pride}^{male} and p_{pride}^{female} by annexing the p^{male} and p^{cub} in p_{pride}^{male} and p^{female} and p^{f-cubs} in p_{pride}^{female} should follow these criteria.

$$f\left(p_{best}^{male}\right) < \left((p_{best}^{male}(pd)\right); \left((p_{best}^{male}(pd)\right) \neq p_{best}^{male} \tag{13}$$

$$f\left(p_{best}^{female}\right) < \left((p_{best}^{female}(pd)\right); \left((p_{best}^{female}(pd)\right) \neq p_{best}^{female} \tag{14}$$

After the selection of best, the mating strength of p_{best}^{male} decides whether to keep p_{best}^{female} in pride or not.

The steps involved in the LA are summarized as follow;

7. Simulation Results

Various simulations are conducted to determine the validity and productivity of our proposed algorithm. All of these simulations are aimed at demonstrating proper and rational scheduling on an industrial scale in order to accomplish our objective. After monitoring industrial energy consumption, these

Step 1: Pride Generation
  Step 1.1: generating territorial male and female as solution constraints
Step 2: Mating
  Step: 2.1: Crossover
  Step: 2.2: Mutation
  Step: 2.3: Gender Grouping
  Step: 2.4: Kill sick/weak cubs
  Step: 2.5: Update pride
Step 3: Territorial Defense
  Step: 3.1: keep the record of cubs age
  Step: 3.2: Do
    Step: 3.3.1: Generate and Transpass
      Nomodic Lion
    Until stronger nomodic lion Transpasses
  Until cubs gets mtured
Step 4: Territorial Takeover
  Step 4.1: Selection of best lion and Lionesses
  Step 4.2: Go to step 2 until termination crietira met

simulation results were retrieved. Six distinct components are managed properly in a multitude of ways, for instance, LOT rated power. Table-1 summarises the overall system of sections, including their numerical values and class type. Due to the limitations of scheduling techniques and the proper load management of shiftable sections, the shiftable sections play a critical role comparable to that of non-shiftable appliances. The simulation results are consistent with the research objectives of low cost, an effective Peak-to-Average Power Ratio (PAR), and a plausible waiting time.

7.1. Daily Average Load

Figure 4 depicts that the daily average load for each algorithm is equal. It means that, the load in un-scheduled case and scheduled with different algorithms, like, GA, CSA, LA and ACO (showed with different colors) is the same. Keeping this common load in mind, simulations are done for knowing the productivity and strength of our suggested algorithm (i.e. LA) and other algorithms which are in comparison with it. This common load will decide which

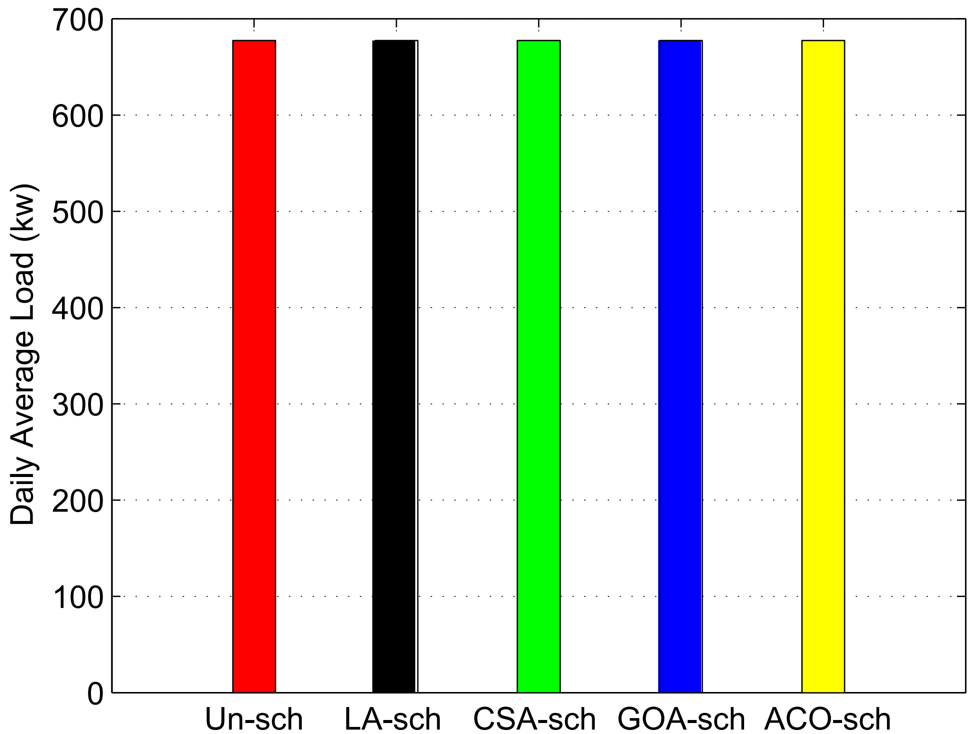

Figure 4: Daily average load graph

method of scheduling is best to get more efficient results. PAR, electricity cost, and waiting time-like factors are observed through this leveled scenario.

7.2. Hourly Load Curves

Figure 5 shows different sketches of hourly load curves, which are drawn for un-scheduled load and scheduled with different bio-inspired algorithms, like, LA, CSA, GOA, and ACO. Their results are compared with unscheduled sketches. It is clear from the figure, that, LA algorithm shifted the load sections from on-peak to off-peak hours, which is not only cost effective but also gives maximum end-user comfort. With different values of appliances power

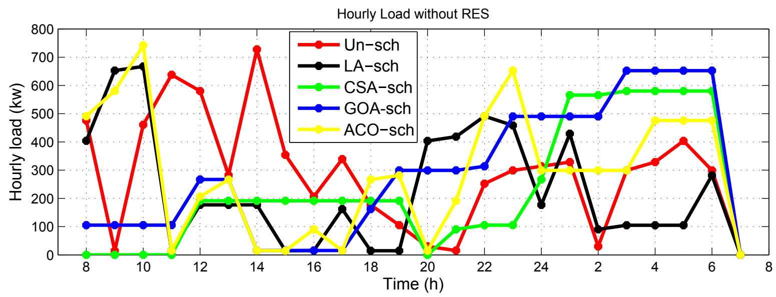

Figure 5: Hourly Load Graph

ratings and their LOTs, our proposed algorithm results are comparatively more acceptable as compare to others.

7.3. Pricing Signal

Numerous global energy systems issue their Real-Time Pricing (RTP) hourly flags on day-ahead basis. Real-time pricing (RTP) signal gives valuable information to both utility and consumer to monitor their usage of electricity. Energy smart meters (SM) provides day-ahead pricing (DAP) signals to the clients, according to which, they manage their daily needs. We have utilized the real-time pricing signal of the New York Independent System Operator (NYISO) [34]. An hourly chart of that DAP signal is graphed in the Figure 6a and Figure 6b. Based on this DAP signal, the cost is calculated.

7.4. Hourly Electricity Cost

Before calculating total electricity cost, it is mandatory to calculate hourly cost, so that, it should be clarified that, in which time interval, the electricity cost is high. Knowing that, the data scheduling process can be made more efficient. In Figure 7 different sketches are drawn which indicate different algorithms. Their peaks and depths, can easily be observed. Compared to CSA, GOA and ACO, Lion's Algorithm (LA) is giving a compensated sketch throughout the day (24 hrs). So LA is stable in case of hourly electricity cost as shown in the Figure 7.

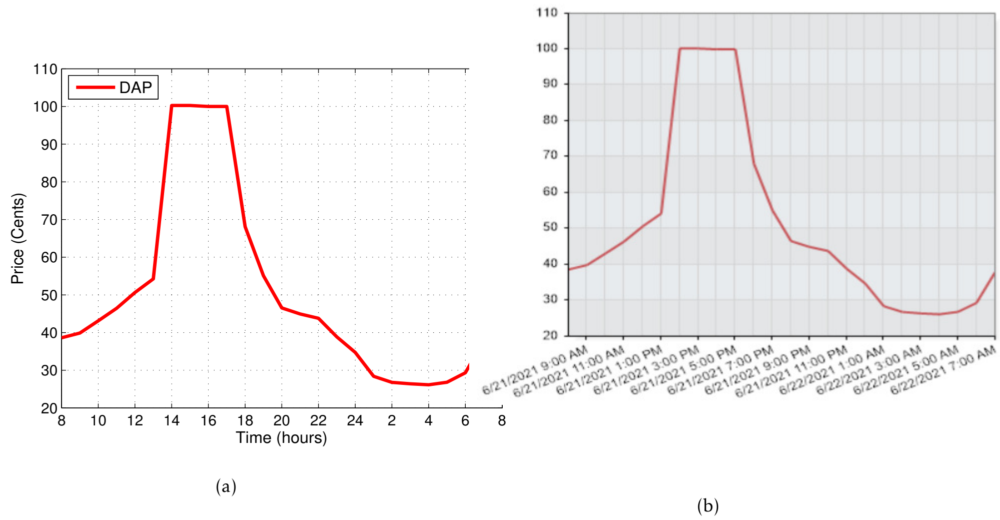

Figure 6: (**a**) DAP Signal (MATLAB), (**b**) DAP Signal (Original) [34].

7.5. PAR simulation

The stability of PAR in electric power systems is the main concern of every researcher. This means that, the system would be stable when PAR is low and vice versa. Figure-8 for PAR values points out that the LA algorithm yields comparatively less value of PAR than all the other optimization algorithms. The CSA Algorithm, GOA Algorithm, and ACO Algorithms optimized PAR to (3% decrease), (13.05 % increase) and (28.72% increase) respectively, while our proposed Lion's Algorithm (LA) decreased it to 35.94 % as depicted in Figure 8, Which was the main concerned of our proposed algorithm.

7.6. Total Daily Energy Cost

Besides resources, one most important factor is cost optimization to provide comfort-ability regarding low energy cost and hence low consumer electricity bill. The more the algorithm is economical, more it will be considered productive. After cost simulation, it is analyzed that the cost of the LA algorithm optimized up to 42.66%. However, CSA, GOA, and the ACO algorithm reduced the cost by 31.81%, 51.13% and 22.79% respectively. This concludes that GOA

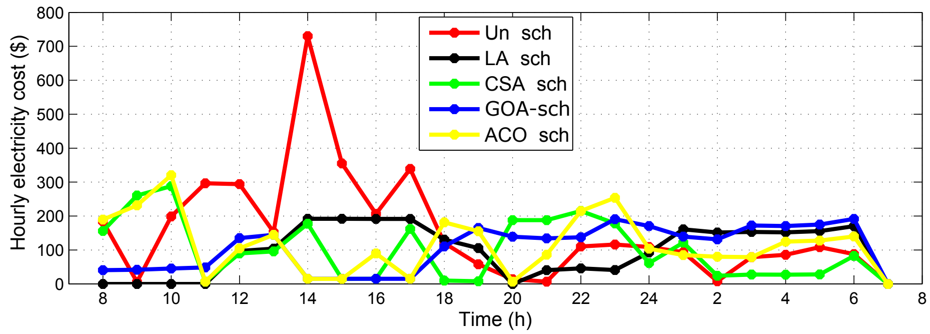

Figure 7: Hourly electricity cost

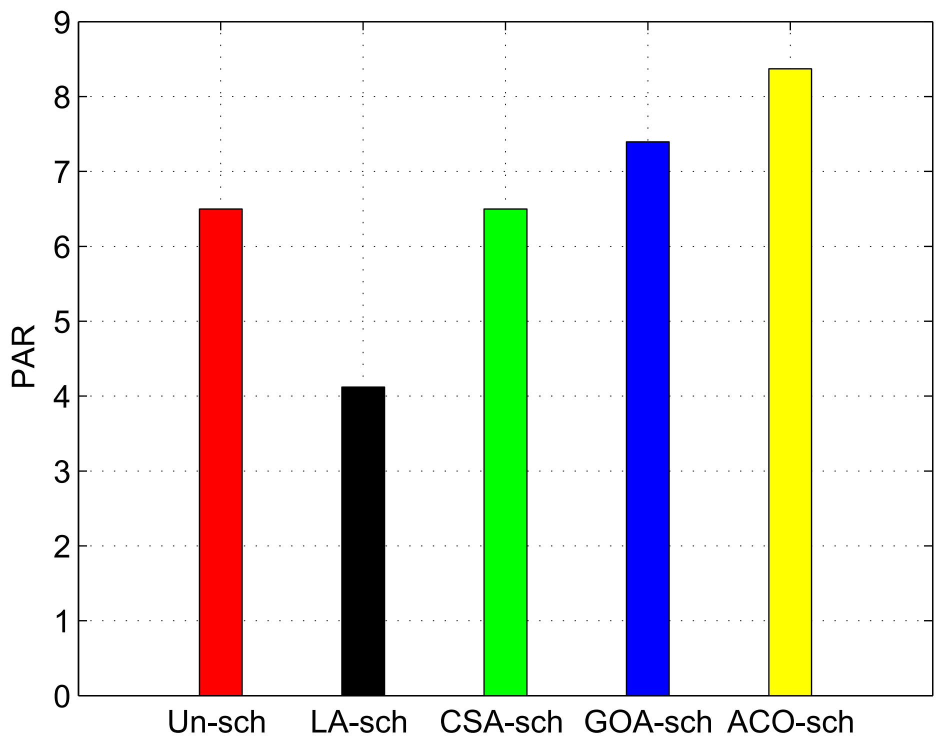

Figure 8: PAR simulation graph

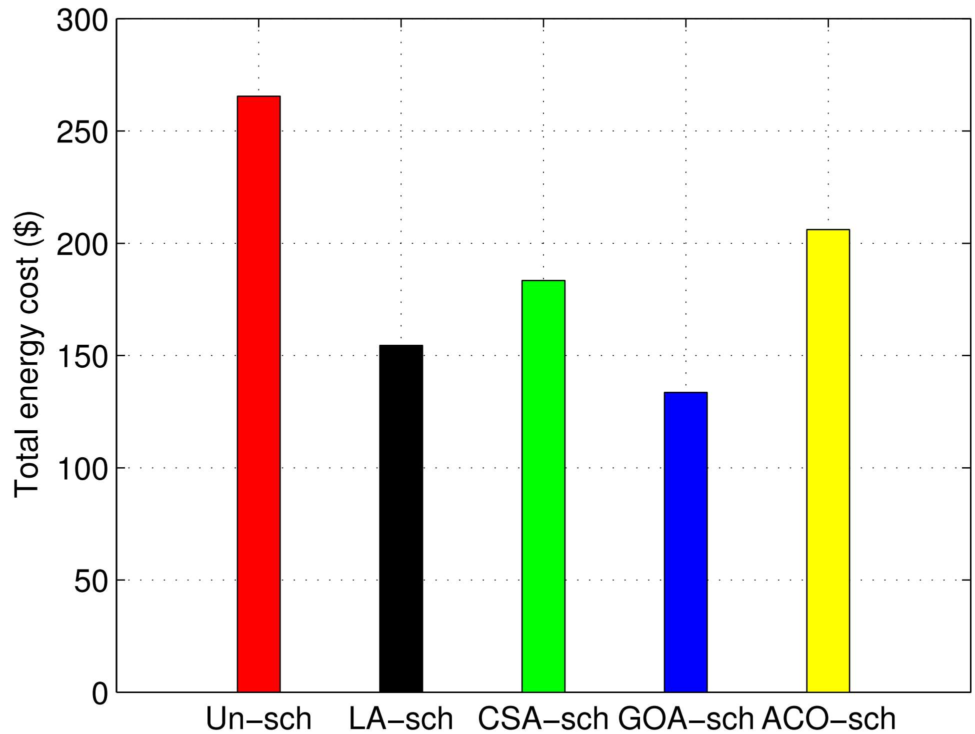

Figure 9: Total Daily Energy Cost

performed well in the case of cost optimization as shown in Figure 9, however, it has reduced the cost with more waiting time, as will be seen in the Figure 10

7.7. Average Waiting Time/ User Comfort

Cost optimization and PAR minimization directly affects the consumer interest. However, they are concerned with the waiting time of load units after making their schedule. This factor (i.e. waiting time of scheduled appliances) is directly related to user comfort when load units scheduling is determined. Figure 10 depicts the average waiting time of machines by different algorithms.

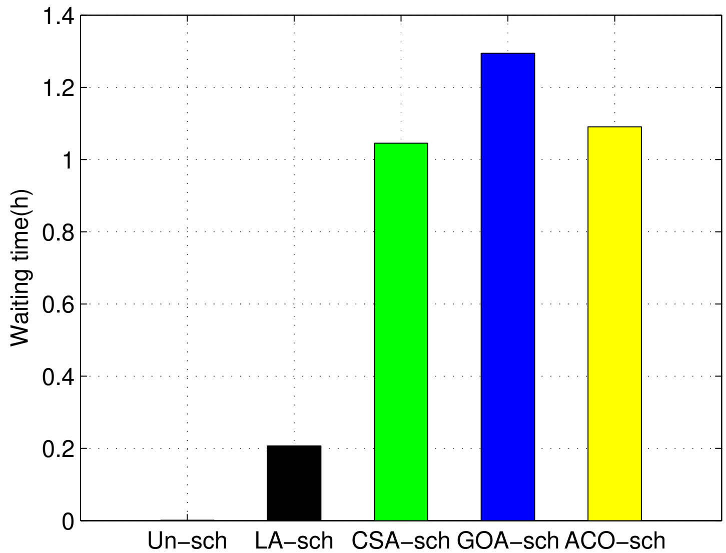

Figure 10: Average Waiting Time

It is clear from the figure that LA outperformed in comparison to all other algorithms. LA gives only 0.216 hrs (12 minutes and 57 seconds) of average waiting time, compared to CSA (1.038 hrs), GOA (1.294 rs) and ACO (1.096 hrs) algorithms.

Table 2 summarizes the performance of the proposed LA algorithm in comparison to the unscheduled-load and load scheduled with the CSA, GOA and ACO algorithms.

8. Conclusion

In this paper, we have proposed a Bio-Inspired algorithm, namely, Lion's Algorithm (LA) for an efficient Energy Management System (EMS) to schedule different industrial load sections for energy optimization and then the results are compared with already existing techniques of CSA, GOA, and ACO. By considering industrial machines power ratings, different LOTs, and Day-

Table 2: Comparison of the proposed algorithm LA with un-scheduled load and scheduled with CSA, GOA and ACO algorithms

Techniques	Cost ($)	%Cost Reduction	Waiting Time (h)	PAR	% PAR Change
Un- Schedule	268.72	–	–	6.51	–
LA Scheduled	154.07	42.66%	0.216	4.17	-35.94 %
CSA Scheduled	183.24	31.81%	1.038	6.49	-0.3%
GOA Scheduled	131.31	51.13%	1.294	7.36	+13.05%
ACO Scheduled	207.46	22.79%	1.096	8.38	+28.72%

Ahead Price signal, we calculated hourly load, hourly energy cost, total daily load, total daily energy cost, PAR and consumer average waiting time. The simulation results show that there is 42.66% decrease in the cost and 35.94% minimization in PAR compared to un-scheduled load. In this work, we not only focused on cost minimization and PAR reduction but mainly concerned with minimized average waiting time, to care of end-user comfort. That is why the proposed algorithm reduced the cost only at 0.216 hrs (12.96 sec). This is a big achievement of the proposed algorithm. This algorithm can be used to realistic data when and where it is needed. In future work, more bio-inspired algorithms will be explored and utilized for achieving better results in term of total cost and PAR reduction, with lowest possible waiting time, and can be applied in all three sectors of society, i.e., industrial, commercial and residential sectors.

Abbreviation

The following abbreviations are used in this manuscript and are presented in alphabetical order:

ACO: Ant Colony Optimization

AM: Analytic Method

AMI: Advanced Metering Infrastructure

AOAs: Automated Appliances

AR: Architecture

BFA: Bacterial Foraging Algorithm

CSA: Cuckoo search Algorithm

DAP: Day ahead Pricing

DSM: Demand Side Management

DER: Distributed Energy Management

DSM: Demand-Side Management

ERD: Energy and Reserve Dispatch

ESS: Energy Storage System

ED: Economic Dispatch

EDE: Enhanced Differential Evolution

EMC: Energy Management Control(ler)

EWA: Earthworm Optimization Algorithm

GA: Genetic Algorithm

GEM: Grid Energy Management

GOA: Grasshopper Optimization Algorithm

HL: Hourly Load

HEM: Home Energy Management

HE: Heuristic

HSA: Harmony Search Algorithm

LA: Lion's Algorithm

LOTs: Length of Operational Time(s)

MDI: Maximum Demand Indicator

MEM: Micro-grid Energy Management

MEO: Micro-grid Economic Operation

MFO: Moth-Flame Optimization algorithm

MH: Math-Heuristic

MVO: Multi-verse Optimization

OPF: Optimal Power Flow

OF: Objective Function

PAR: Peak to Average power Ratio

PSO: Particle Swarm Optimization

RDG: Reconfiguration of Distribution Grid

RTP: Real Time Pricing

SA: Solution Algorithms

SDN: Smart Distribution Network

SG: Smart Grid

SM: Smart Meter

SSM: Supply Side Management

TEC: Total Energy Cost

TG-MFO: Time-constrained Genetic Moth-Flame Optimization

TN: Taxonomy UC: Unit Commitment

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