# Network Signal Analysis for Engineering Multitrophic Plant Health Communication Systems

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***Abstract*—Sustainable agriculture is increasingly dependent on the soil microbiota to reduce synthetic chemical inputs. Entomopathogenic nematodes (EPN) and plant growth–promoting rhizobacteria (PGPR) are promising agents for pest control and plant health enhancement, yet their co-culture poses design challenges. This work models an EPN–PGPR co-culture as a multitrophic network and applies graph signal processing to analyse interaction dynamics. The results reveal storage-induced structural fragilities and provide a principled basis for optimising experimental design, supporting robust development toward scalable, sustainable plant health applications.**

***Index Terms*—nematodes, bacteria, communication networks, graph signal processing**

## I. Introduction

In recent years, researchers have been investigating novel methods that promote plant health while reducing dependence on synthetic chemical products [1]. To this end, engineering biological agents, such as entomopathogenic nematodes (EPNs) and plant growth-promoting rhizobacteria (PGPR), are being considered sustainable alternatives due to their ability to control pests and improve plant growth [2]. However, little to no research has documented EPN-PGPR co-culture experiments and their combined effects to promote plant health. To bridge this gap, we designed an EPN-PGPR co-culture experiment and represented it using a multitrophic network model to investigate the effects of the different biophysical requirements of the individual biological agents.

In this work, node states represent signalling-relevant biological conditions, and edge weights encode effective communication gains or impairments through which biochemical influences propagate. Although the proposed model does not explicitly simulate molecule-level diffusion or receptor kinetics, it provides a network-level abstraction of molecular communication within the EPN–PGPR co-culture. We apply graph total variation and spectral energy ratios (graph signal processing – GSP metrics) to quantify how storage-related biophysical variables (e.g., temperature, moisture, oxygen, and nutrients) perturb this communication network. Here, storage stress is viewed as a structured channel interference, and the measurement of its effects can lead to a more robust biological communication topology, accelerating the development of a sustainable plant health agent.

This research was funded by the South East Research Development Fund, grant number SERD2021CW PES1441.

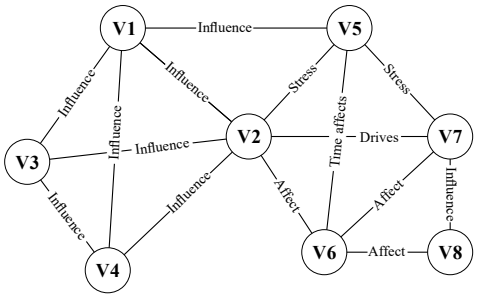


Fig. 1: Multitrophic network model for an EPN-PGPR co-culture experiment.

## II. Multitrophic Network Model

The multitrophic network model is based on wet lab experimentation on the EPN-PGPR co-culture while encapsulated in an alginate medium. Each network node is an actor investigated in the experiment that impacted the effectiveness of the EPN-PGPR co-culture, and is defined as follows: $V1$ and $V2$ are encapsulated EPN and PGPR; $V3$ and $V4$ are the size and composition of the encapsulation beads; $V5$ and $V6$ are the storage conditions and duration; and $V7$ and $V8$ are the survival levels of EPN and PGPR. Each directed edge is assigned a real-valued weight that encodes both the magnitude and the polarity of the interaction, with positive values representing promotion effects and negative values representing inhibitory effects based on the qualitative descriptors shown in Figure 1. The weights are kept constant across the simulation scenarios, so the differences in system behaviour reflect the variations in exogenous storage conditions rather than changes in network topology.

Based on the multitrophic network shown in Figure 1, the encapsulated EPN-PGPR culture is represented as a directed influence network $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with $N = |\mathcal{V}|$ nodes corresponding to design variables, storage conditions, and biological survival outcomes. At each discrete time step $t$, the system state is collected in $\mathbf{x}(t) \in [0,1]^N$, which is interpreted as a graph signal defined in $\mathcal{G}$. Each component $x_i(t)$ represents a normalised measure of viability, concentration, or survival associated with the node $i$.

Let $W \in \mathbb{R}^{N \times N}$ denote the weighted adjacency matrix of $\mathcal{G}$,where $W_{ij}$ quantifies the influence of node $j$ on node $i$. To

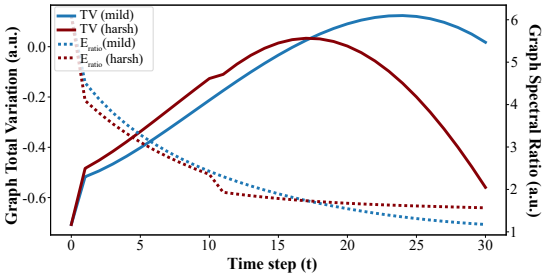


Fig. 2: GSP metrics considered on the analysis of the proposed multitrophic network model of an EPN-PGPR co-culture. In the legend, TV refers to the graph total variation and $E_{ratio}$ refers to the graph spectral ratio.

enable a real-valued spectral decomposition, a symmetrised graph shift operator that preserves the magnitude of pairwise interactions is defined while discarding directionality for the purposes of spectral analysis. The graph shift operator $W_s$ is defined as $W_s \triangleq \frac{1}{2}\left(W + W^\top\right)$. From $W_s$, the combinatorial graph Laplacian $L \triangleq D - W_s$ is constructed, where $D = \mathrm{diag}(W_s\mathbf{1})$ is the degree matrix, and $\mathbf{1}$ is a unitary matrix. The Laplacian is used to quantify the smoothness of the evolving biological signal over the multitrophic network. Specifically, the graph total variation (TV) of $\mathbf{x}(t)$ is defined as [4]

$$\mathrm{TV}(\mathbf{x}(t)) \triangleq \mathbf{x}(t)^\top L\, \mathbf{x}(t). \tag{1}$$

Low values of $\mathrm{TV}(\mathbf{x}(t))$ indicate a coherent and spatially smooth behaviour in the multirophic network, whereas larger values reflect localised heterogeneity and uneven degradation patterns.

To characterise how storage-induced disturbances propagate through the multitrophic network, $W_s$ is initially decomposed into eigenvectors as $W_s = U\Lambda U^\top$, where $U = [\mathbf{u}_1, \ldots, \mathbf{u}_N]$ is an orthonormal basis of graph Fourier modes and $\Lambda = \mathrm{diag}(\lambda_1, \ldots, \lambda_N)$ contains the associated graph frequencies. After performing a graph Fourier transform (GFT) of the network's state, given by $\widehat{\mathbf{x}}(t) = U^\top \mathbf{x}(t)$, decomposing the GFT coefficients into low- and high-frequency components. Let $\mathcal{I}_\ell$ and $\mathcal{I}_h$ denote the index sets corresponding to the lower and upper halves of the spectrum, respectively, associated spectral energies are then defined as [4]

$$E_\ell(t) \triangleq \sum_{i \in \mathcal{I}_\ell} \widehat{x}_i^2(t), \qquad E_h(t) \triangleq \sum_{i \in \mathcal{I}_h} \widehat{x}_i^2(t). \tag{2}$$

The graph energy ratio $E_{ratio} = E_h(t)/E_\ell(t)$ serves as an indicator of spectral redistribution from global smooth modes to localised network modes.

The simulation of the multitrophic network model also requires the inputs of the storage conditions scenarios (mild and harsh) incorporated through a latent storage index that aggregates multiple normalised environmental variables into a single bounded graph signal. Specifically, storage-related covariates such as temperature, humidity, light exposure, and oxygen availability are normalised to $[0, 1]$ and combined via a weighted sum, followed by a logistic mapping to ensure boundedness. The resulting index captures the relative severity of storage conditions, with larger values indicating harsher environments. The weighting coefficients encode the relative sensitivity of the system to each variable, while a bias and gain parameter set the nominal operating point and transition steepness. This formulation provides a continuous, differentiable representation of storage effects suitable for spectral and graph-based analysis.

## III. Preliminary Results

The behaviour of the multirophic network model was evaluated by observing the temporal evolutions of $\mathrm{TV}(\mathbf{x}(t))$ and $E_{ratio}$ considering mild and harsh storage scenarios (Figure 2). This analysis reveals how exogenous variables that affect storage conditions modulate the spatial coherence and spectral composition of survival-related signals, allowing the identification of structurally localised vulnerabilities in the encapsulated system. In Figure 2 it can be seen that TV under mild storage conditions took longer to reduce compared to the harsh storage scenario, denoting that storage stress propagates through specific biological pathways rather than uniformly affecting all components. It can also be seen that $E_{ratio}$ in the mild storage scenario leads to a continuous decrease over the observed time period, while in the harsh storage scenario, the network state vector has more high-frequency components resulting in a bumpy decrease of $E_{ratio}$, hitting a floor after $t = 10$.

The results obtained indicate that encapsulation design variables play a critical role in constraining storage-induced stress to low-frequency, globally coherent modes. The observed shift toward high-frequency activation under harsh storage conditions highlights design-mediated fragilities, implying the need to improve our experimental protocol for the EPN-PGPR culture.

## IV. Conclusions

In this work, graph signal processing metrics were utilised to investigate the experimental design of an encapsulated EPN-PGPR culture intended for the development of a plant health agent. The graph spectral analysis suggests a direct analogy between robust network design in communications and experimental design in wet-lab biological systems, which will be helpful to optimise the design, duration and effectiveness of the plant health agent.

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