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Data-Driven Network Graph Theory for Controlling Dynamic Systematic Data Perspective of Smart Power

K. Basari Kodi[1], M. Mano Raja Paul[2], M. Geetha[3], G. Nallasivan[4], S. Jeevitha[5] and A. Bhuvanesh[6]

[*1]*Department of Mathematics, Ramco Institute of Technology, Rajapalayam, Tamil Nadu, India; basarikodi@outlook.com*
[2]*Department of Electrical and Electronics Engineering, Nehru Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India; manorajapaul273tn@gmail.com*
[3]*Department of Electrical and Electronics Engineering, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu, India; geetha374eee@outlook.com*
[4]*Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D institute of Science and Technology, Avadi, Tamil Nadu, India; nallasivan751@gmail.com*
[5]*Department of Computer Science and Information Technology, Kalasalingam Academy of Research and Education, Krishnankoil, Tamil Nadu, India; sjeevitha78cs@mail.com*
[6]*Department of Electrical and Electronics Engineering, PSN College of Engineering and Technology, Tirunelveli, Tamil Nadu, India; abhuvanesh46332psn@mail.com*

***Correspondence:** *basarikodi@outlook.com*

ABSTRACT- To attain sustainable energy in the increasing climatic adaption and environmental defence, the predominant factor to attain is smart power generation which ensures the secured operation economically. The dynamic nature of the power in the system scale explicitly shows the limitations of the conventional first principle model. To tackle this issue, we propose a Network Graph theory (NGT)-based mathematical modelling incorporated with the data-driven control (DDC) and to attain the optimal output the NGT is optimized using the proposed Mayfly optimization algorithm (MO). This proposed technique is utilized to analyze the uncertainty with fault detection and diagnosis. The factors for controlling the smart power system are discussed and we presented the technique for the fault detection and diagnosis. Simulation demonstrates and analyses the different factors such as detection accuracy. Recall, and precision with the state-of-art techniques. The proposed techniques pave the way for protecting smart power generation along with dynamically controlled systematic data.

Keywords: Smart power, Dynamic systematic data perspective, Data-driven, Graph theory algorithm.

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1. INTRODUCTION

Smart power [1] is defined as a strategy that emphasizes the need for effective armed forces but also makes significant investments in collaboration, coalitions, and organizations at all stages to increase power while strengthening the veracity of behavior. Something that makes use of technology to make the globe an environmentally friendly place is referred to as smart energy [2]. It uses renewable electricity to save money and make the entire globe a greener place. The technique of employing gadgets to reduce utility bills is known as efficient power. It emphasizes strong, long-lasting renewable energy resources that reduce expenses and encourage increased sustainability.

Energy efficiency [3] can be attained with the use of the building's comprehensive, sophisticated power control platform. Structures can be made smarter by utilizing technologies like intelligent detectors and the utilization of clean energy sources. It results in less resource waste and better ecological circumstances. The Sensible Energy-Trading device communicates with a residence monitoring module and is intended to start operations on its own. Using dispersed green power resources, the program independently controls the production, usage, and transmission of environmentally friendly energy. To reduce greenhouse gases and safeguard the environment, humanity must build renewable energy infrastructure, which requires the use of sophisticated renewable energy sources, by creating creative approaches like carbon absorption and lowering carbon footprints.

A collection of houses with photovoltaic cells placed on the roofing material, an assortment of electric automobiles that can recharge cooperatively during periods of substantial energy efficiency, or a battery that uses a lithium-ion memory are a few instances of potential socioeconomic status gadgets. The ability to communicate that the network offers through a Smart Energy Management (SEM) [4] device is one major facilitating innovation that tracks, measures, controls, and improves the use of electricity across the structure. The idea of a sophisticated power platform is concluded to signify advancement in science that is moving beyond the single-sector perspective and toward an integrated comprehension of power networks and the ability to exploit the coordination of all facilities and domains.

An electrical source with greater variety decreases the production of greenhouse gases and airborne pollutants, the increasing shift away from environmentally damaging conventional sources of power. It is risky to attempt to solve this issue by connecting wires for extension or additional electrical panels; it could lead to an electromagnetic disaster or possibly harm electronic devices. To ensure control over the dynamic systematic data in smart power generation we have proposed a Network Graph theory-based Mayfly optimization algorithm.

The rest of the work is arranged as the literature review is enclosed in *section 2*. The proposed methodology for the controlling of smart power generation is enclosed in *section 3*. The experimental analysis is made in *section 4*. The work is concluded in *section 5*.

2. LITERATURE SURVEY

Antonopoulos et al. [5] have presented Artificial Intelligence (AI) methods employed for deep learning systems. This results from a methodical examination of over sixty publications, forty business ventures, and twenty substantial enterprises. While AI techniques provide several capabilities to address several of the strategies' concerns, they also present some issues and constraints. For the procedures to be properly applied in the environment, an improved awareness of these limits is essential. In the power industry, following this approach will enable AI methods to develop into standard operating procedures or standards. Hence, a lot of the suggested solutions haven't been validated by extensive, real-world investigation.

Merabet et al. [6] have described Artificial Intelligence (AI) techniques for Business Energy Administration Solutions (BEMS) that allow heating and cooling to be taken into account along with environmental sustainability. Additionally, evaluations of the applications of the strategies carried out were analyzed, and the requirements for inclusion determined the results of AI-based strategies in conserving energy and climate augmentation. Its efficacy usually stands next to conventional regulation, and the difference dwells mainly in the reality that more knowledge of the framework is available. This category of supervisory methods emphasizes encounter and target to achieve straightforward, adaptable, and successful surveillance. Therefore, it does not give special attention to classifying the techniques.

Aguilar et al. [7] have developed artificial intelligence techniques, using an independent technology standpoint, to achieve successful energy administration. These assignments must make it possible to comprehend and analyze the events taking place on the monitored network. As a result, conceptual frameworks are created throughout these processes to comprehend the framework. It can determine the location of the investigation as well as provide a graphic representation of the possibilities and hurdles that exist in each sector. Moreover, the device construction process does not follow a particular technique.

Kathirgamanathan et al. [8] suggested that Data-driven predictive control (DDPC) is anticipated to be an architecture that makes this closure of the circuit possible in situations where scaling appropriate physics-based systems for controlling the structure is feasible. The majority of preventive management tools undergo validation and testing solely on substitute models. The device and simulation's ability to respond to actual unpredictable changes in addition to how simple it is to integrate with construction control technologies. Thus, it is impossible to generate appropriate representations of the structure through automation.

Sun et al. [9] highlighted machine learning (ML) and data-driven control (DDC) methods as a better substitute for these antiquated techniques. It can greatly improve the accessibility of the basic power structures when combined with continuous assessment. The enforcement layer can increase the object's mobility by applying an appropriate approach to a particular kind of unpredictable interruption determined by the availability of data. It can be integrated into the paradigm to increase energy production networks' resilience in describing variability. Hence, it is ineffective at detecting high-order functions.

3. PROPOSED TECHNIQUE FOR CONTROLLING DYNAMIC SYSTEMATIC DATA PERSPECTIVE OF SMART POWER

For controlling the dynamic systematic data perspective of smart power several parameters are considered. Some of the factors are Visibility and maneuverability, Flexibility and profitability, and safety and this section explains them in detail.

3.1. Visibility and Maneuverability

The dynamic nature of the visibility are characterization of the quantitative process and the soft sensing of hidden variables. The primary dynamic parameter is the inevitable stochastic noise and on the other hand, maneuverability is the identification process of the evaluated signals from the visibility level with the objective of dynamic disturbance rejection.

3.1.1. Dynamic quantitative characterization

The system identification approach is used for the characterization of the system's dynamic nature. However, it is equivalent to the black box with the physical modeling nature. It can be utilized to characterize the framework and structure of input and output parameters for the generation of power with the control input activations. Meanwhile, the most commonly used technique for power plants is traditional step response-based transfer function identification. This is mainly used in the regenerative heater, multivariable fluidized bed combustor, and the identification of fuel cell temperature. If there is more noise, the identification of high-order is incapable with the respective technique. Hence to tackle the issues, it is recommended the artificial technique.

3.1.2. Soft sensing

For the estimation of critical variables in energy systems, soft sensing techniques have been utilized along with the algebraic correlation of DD. This can be used for the visualization of internal phenomena and estimated feedback signals. Sometimes, the state evaluation in the model has more noise and dynamics and leads to low accuracy. To tackle this, battery core temperature evaluation along with the state augmentation and correction of feedback are included in the traditional DD techniques.

3.1.3. Regulatory control

The regulatory control level is utilized for the implementation of strong maneuverability along with the deployment of feedback controllers. The sensed signals from the visibility level are received at this level along with the reference commands from the topper at most levels. This level aims to reduce the dynamic disturbances along with the unmeasurable impacts. The designing of loop and feedback controllers for each component is a time-consuming technique and economically high and to mitigate these issues, the DD control technique (ILC, PID controller, etc.,) is used.

3.2. Flexibility and Profitability

The coordination of operation of multiple loops is controlled with the capacity is referred to as flexibility and is the ground truth of the profitability. The main purpose of profitability level is obtaining the maximum profit and minimal costs with the optimal constraints. More flexibility means it is easy to maintain interactive energy systems with the highest economic efficacy.

3.2.1. Flexibility

The flexibility of the supervisory control level is used for linking the basic regulatory loops. The dynamic transition is attained economically with the flexible multivariable controller design. For the supervisory control design, the multivariable model is essential for power generation. To achieve this, the DD technique has been applied by many researchers. However, it has some limitations and to tackle this Artificial intelligence technique has been used along with the DD technique.

3.2.2. Profitability

Profitability is the main factor in designing the power generation systems. Data mining is the conventional technique used for the achievement of profitability with historical data. However, to optimize profitability artificial intelligence-based optimization techniques have been used nowadays.

3.2.3. Safety

Smart power generation is modeled in two classes: (i) model-based and (ii) DD-based. The former one provides the quantitative relationship between the inputs, states, and outcomes which is used for identifying the uncertainties. The residual between the outcome and the projections is evaluated. For detecting the faults some effective technique is necessary to ensure safety. This technique used an NGT-based MO algorithm.

3.3. Network Graph Theory (NGT)

The fault diagnosis is performed using NGT. The subject to potential device uncertainties with plant outputs, states, and input to the quantitative relations are sought with this model approach. When the prescribing threshold is greater is to accumulate residual thereby detecting and isolating faults. While focusing on the neighbor nodes, the local properties are analyzed with the biological networks represented via a large graph [10]. The degree is the percentage of vertices and is displayed via the graph degree distribution of fault diagnosis. The degree is D that randomly selects the probability distribution of degree is outlined as;

$$pro(D) = \frac{\delta_D}{\delta} \tag{1}$$

The degree vertices are δ_D. The structure of general data is provided with the graph density. The adjacency list represents some connections among its vertices and the space graph is noted. The possible number of edges$pro(g)$ shows the graph density is g.

$$pro(g) = \frac{2n}{m(m-1)} \tag{2}$$

Where, $2n$ is the undirected graph summation degrees of fault diagnosis. Connect the neighbors and it describes the vertex of clustering coefficient.

$$clu(VR) = \frac{2R}{D(D-1)} \tag{3}$$

Where, VR is the nearer node graph denoted as the density D. By all the neighbors, comparing their common neighbors related to two nodes is called matching index. The two nodes in a graph's similarities are shown via matching index parameters.

According to the complex network, the significance of edges or nodes is determined as the centrality. Over the nodes, the shortest paths are calculated to evaluate the centrality parameter of fault diagnosis. The summation of distance from VR to another node to calculate the node closeness centrality.

$$Cen(VR) = \frac{1}{\sum_{VR\in U} dis(U,VR)} \tag{4}$$

Where, $dis(U, VR)$ is the vertices distance. The significance of node VR is determined by using the node vertex between centrality.

$$bc(VR) = \sum_{S\neq t\neq vr} \frac{\alpha_{ST}(VR)}{\alpha_{ST}} \tag{5}$$

The amount of shortest way among each node S and T isα_{ST}. Calculate the shortest paths via the edges and the vertex between centrality is similar to the vertex between centrality. An external or internal event that affects the deviation or variation of its function is the biological system perturbation. According to the biological network, the perturbations affect mutations and the fault diagnosis performance. Hence, we suggested the Mayfly Optimization (MO) algorithm to boost the performance of NGT for the diagnosis of faults.

3.4. Mayfly Optimization (MO) Algorithm

The Ephemeroptera order insects are Mayflies and it is visible to the naked eye is immature mayflies next hatch from the egg. The working characteristics of mayflies inspire the Mayfly Optimization (MO) algorithm along with NGT for fault diagnosis. Based on the neighbors, adjust each male mayfly position that implied the male collections in swarms [11]. At step *t*, the mayfly's current location is y_j^t and vl_j^{t+1} is the velocity to change the position are described as;

$$y_j^{t+1} = y_j^t + vl_j^{t+1} \quad (6)$$

Calculate the j^{th} male mayfly velocity is vl_j^{t+1}. The following formula calculates $Be_{po_{jk}}$ is the personal optimal position at *t+1* step time.

$$Be_{po_{jk}} = \begin{cases} y_j^{t+1}, if F(y_j^{t+1}) < F\left(Be_{po_j}\right) \\ Keepitsimilar, Otherwise \end{cases} \quad (7)$$

Where, Be_{po_j} and y_j are the Cartesian distance as P_r and the following formula computes the distance.

$$\|y_j - Y_j\| = \sqrt{\sum_{k=1}^{m}(y_{jk} - Y_{jk})^2} \quad (8)$$

At step time *t* in the search space, the female mayfly's current position is y_j^t. The current position velocity vl_j^{t+1} to change the position.

$$z_j^{t+1} = z_j^t + vl_j^{t+1} \quad (9)$$

Randomize the process of attracting female mayflies' movements. The best male attracts the best female based on the function of fitness. Compute the velocity to consider the minimization issues.

$$v_{jk}^{t+1} = \begin{cases} vl_{jk}^t + b_2 e^{-\eta r_{Nf}^2}(y_{jk}^t - z_{jk}^t), if F(z_j) > F(y_j) \\ vl_{jk}^t + FL * R, if F(z_j) \le F(y_j) \end{cases} \quad (10)$$

The j^{th} female position in k^{th} dimension is vl_{jk}^t. The coefficient of fixed visibility is η with Cartesian distance among the female and male mayflies are R_{nF}.

Select the population of male (*ma*) from female (*Fe*) with respect to one parent. The males attract the females and the similar is to select the way parents.

$$off_{spring-1} = ma * l + (1-1) * Fe \quad (11)$$

$$off_{spring-2} = Fe * l + (1-1) * ma \quad (12)$$

Set zero as the initial velocities of offspring thereby demonstrating the best solution to enhance the performance of NGT during fault diagnosis. Compared to the historical operational data, the proposed MO algorithm with NGT effectively diagnoses faults by neglecting uncertainty difficulties.

4. EXPERIMENTAL DISCUSSIONS

This section explains to develop a reliable, accurate, and fast fault detection technique for the protection of power generation systems. The comparison is handled by using existing comparative studies like AI [5], BEMS [6], DDPC [8], and MI [9] thereby describing proposed work performance. MATLAB SIMULINK executes the simulation part of the proposed work.

4.1. Performance Validation

Figure 1 outlines the proposed performance based on various measures. To enhance reliability and accuracy, the simulation results are given by proposing a fault detection model. With and without fine-tuning, the NGT method depends upon the approach of fault diagnosis. The accuracy is calculated with the true label results. The length of convergence falls under 100 to 600 ranges based on the number of iterations. Both training and testing hold 70% and 30% of data.

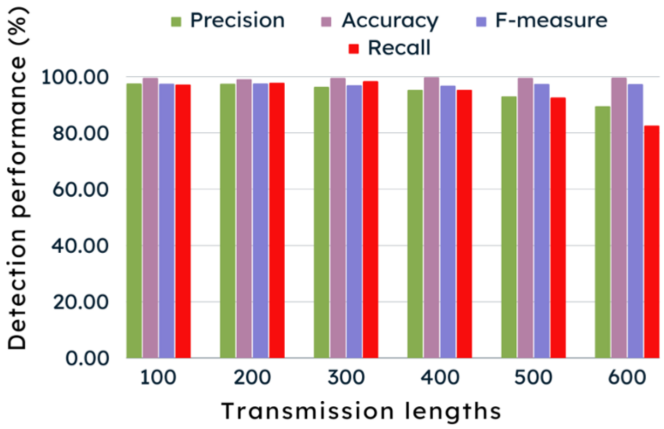

Figure 1. The proposed performance based on various measures

The proposed training time is displayed in *figure 2*. The proposed model dedicates the fault estimation training time to be decreased. The target and source dataset values are enhanced and increase the variation among the length. The proposed methodology training time depends upon the training time to demonstrate the classification results. Greatly reduce the overall error values through the process of tuning considering few time values.

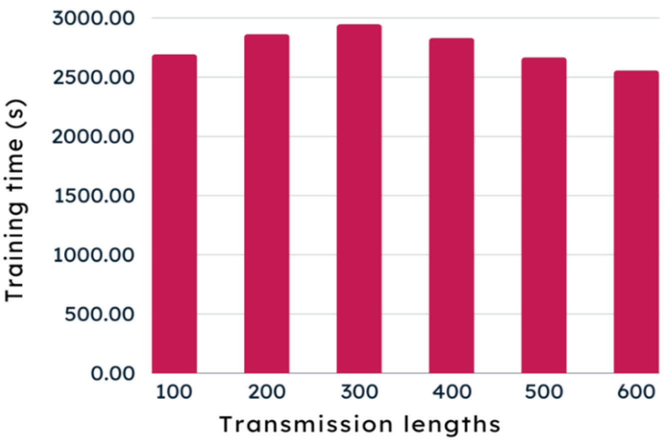

Figure 2. The proposed performance based on training time

Table 1 shows the overall testing accuracy of comparative outputs. Compared with other existing techniques like AI [5], BEMS [6], DDPC [8], and MI [9], we have attained higher and better overall accuracy of the proposed due to the good fault diagnosis models. According to fault diagnosis, the proposed determined 98.67% from the process of classification.

Table 1. The accuracy of comparative results

Techniques	Accuracy in percentage
AI [5]	78.61
BEMS [6]	88.75
DDPC [8]	84.22
MI [9]	89.04
Proposed	98.67

Figure 3 displays the comparative investigation of accuracy. The previous studies namely AI [5], BEMS [6], DDPC [8], and MI [9] proposed frameworks to compute the percentage levels of accuracy. While raising the length of transmission lines to get the increasing number of percentages in terms of accuracy. Therefore, this graphical plot reveals that the proposed work accuracy is higher and superior to that of previous AI [5], BEMS [6], DDPC [8], and MI [9] approaches.

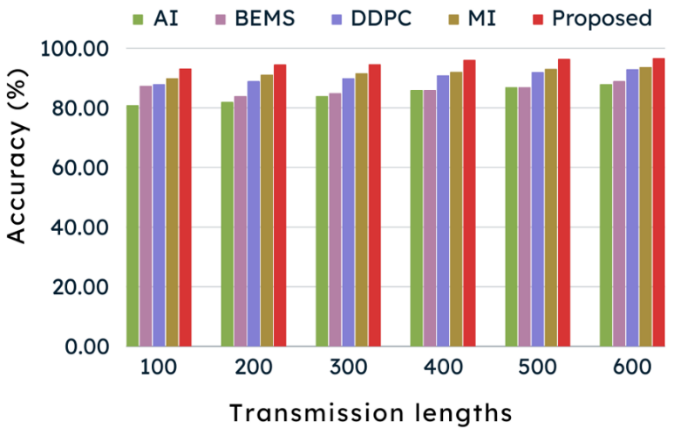

Figure 3. Comparative investigation of accuracy

Figure 4 delineates the comparative investigation for precision. The previous studies namely AI [5], BEMS [6], DDPC [8], and MI [9] proposed frameworks to compute the precision levels. While raising the length of transmission lines to get the increasing amount of precision percentages. Hence, this graphical plot reveals that the proposed work efficiency of precision becomes greater than that of previous AI [5], BEMS [6], DDPC [8], and MI [9] approaches.

The recall results with its comparative plot are illustrated in *figure 5*. The earlier studies namely AI [5], BEMS [6], DDPC [8], and MI [9] proposed a framework to execute the percentage levels of recall. While raising the length of transmission lines to get the increasing number of percentages in terms of recall. Therefore, this graphical plot reveals that the proposed work recall output is higher and superior to that of previous AI [5], BEMS [6], DDPC [8], and MI [9] approaches.

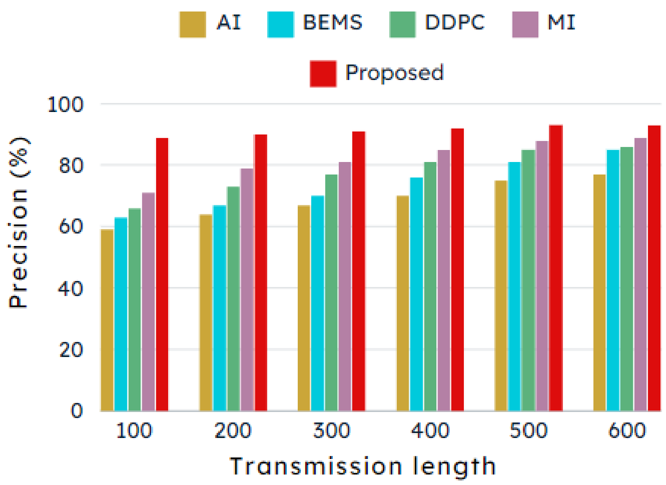

Figure 4. Comparative investigation of precision

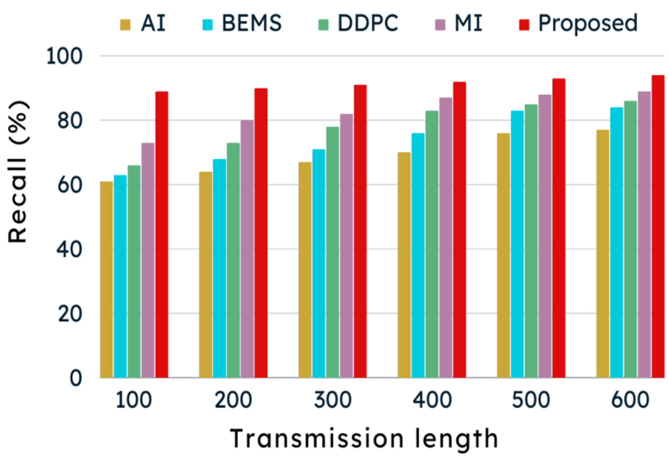

Figure 5. Comparative investigation of recall

5. CONCLUSION

This work presented a novel technique for the control of power generation in the dynamic systematic data perspective. The work presents the factors responsible for smart power generation along with the technique known as NGT-MO incorporated with the DD. This work ensures the safety of power generation with the identification of faults in the power generating system which controls the uncertainty issues. The proposed method is validated using the experiments and analyzed the effectiveness. A comparative study is made with state-of-art works and analyzes the statistical parameters such as accuracy, recall, and precision. Further, the proposed techniques overcome all the existing issues presented in the factors to be solved to attain controlled smart power generation.

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