Leveraging Graph Digital Twin for Fault Detection and Improved Power Grid Stability in Smart Cities

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Abstract. Despite the critical role played by power grids in smart cities, traditional systems often detect issues too late leading to costly outages and safety risks. This paper presents a novel approach by leveraging graph-based digital twins created with the help of Microsoft Azure IoT TwinMaker to enable an always-on view of real-time power grids. For one to derive a virtual model of this grid that reflects what happens in its counterpart in the physical plane, digital twins have this application. Simulation of the grid's behavior helps reveal existing problems to operators without affecting the infrastructure. The system incorporates advanced machine learning techniques, including a genetic algorithm, which can predict failures in advance by taking realtime and previously recorded data from the digital twin. This approach is proactive, thereby preventing disruptions and operational risks. It ensures scalability and efficient processing of large datasets when running machine learning models in the cloud on Microsoft Azure, thus adapting the system to the complex needs of modern power grids in smart cities. Using machine learning in the digital twin rather than in the physical grid minimizes real-world testing and avoids unanticipated downtime, thereby saving costs. This approach not only enhances the accuracy of fault detection but also improves the lasting ability and steadiness of the grid. The solution aims to support the rising energy demands of smart cities by offering a scalable, cost-effective, and reliable way of managing power grids.

Keywords: Digital Twin · Smart Cities · Fault Detection · Power Grid Stability · Graph Digital Twin · TPOT · Machine Learning · Azure IoT TwinMaker

1 Introduction

The increasing complexity and strong demand for a stable power supply in smart cities call for innovative approaches to the management of grids. This project aimed at addressing these issues in light of using digital twin technology, specifically in graph-based digital twins, to generate real-time dynamic models for key

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components of the power grid. A graph-based digital twin mirrors the very intricate interconnections associated with the grid and could potentially be utilized to gain further insights into its operations[1].

A key feature of this project is the graph-based representation of various components of the power grid, which means intuitive modeling can be represented if there are relationships amongst various parts of the grid. Hence, it should be possible to create mappings of interaction between the interactions between the generators and critical nodes with transformers when considering the complexity of mapping it into a graph-based model of a digital twin for the power grid[2]. This approach gives a better insight into the behavior of the grid, thus fast detection of faults, downtime, and inefficiencies. Additionally, with graph theory, algorithms are developed to detect anomalies and faults, thus improving the stability and resilience of the grid.

The rich dataset feeds into the digital twin, which allows the machine learning models to make predictions based on the analyzed patterns[3].

At the heart of our predictive capabilities lies the use of machine learning algorithms specifically, a genetic algorithm, to predict potential faults[4]. Such algorithms analyze the collected data and ensure optimized functioning of the grid by detecting weaknesses before they develop into large failures.

The scope of this project extends beyond the mere detection of faults. Our system is built to make power grids more interoperable in smart cities, compatible with the existing infrastructure of a smart city[5]. That is, our solution can be integrated with other digital systems in the city, such as transportation, communication, and water supply networks, making the urban environment more connected and efficient. Such an approach would, therefore, be crucial in offering solutions to the existing particular challenges in smart cities, where different systems must be interconnected and function in harmony with each other seamlessly.

The rest of this paper is organized as follows: Section II covers related work and technologies. Section III presents the system architecture and methodology. Section IV discusses the machine learning techniques used. Section V provides experimental results and analysis. Finally, Section VI concludes the paper with a summary and future directions.

2 Related Work

2.1 Power Grid Monitoring Systems

Continuous and stable operation of electric networks calls for power grid monitoring systems. It enables the operators to monitor the actual performance of the grid, detect anomalies, and take corrective actions to avoid or minimize outages. In modern power grids where the coallition of renewable sources of energy, electric vehicles, and smart technologies has increased the complexity, effective monitoring systems are in demand. While the approaches used in monitoring

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traditional power grids have been perfected with time, they are limited and prevent them from effectively preventing failures and interruptions[6]. Traditional approaches followed along with their limitations are as follows.

Supervisory Control and Data Acquisition (SCADA) Systems The most common technology applied in power grid monitoring is the Supervisory Control and Data Acquisition (SCADA) system. Supervisory Control and Data Acquisition systems are centralized networks that collect data from sensors dispersed throughout the grid and give real-time information to operators. These systems monitor a range of parameters, such as voltage levels, current flow, and equipment status, and help operators manage grid operations. However, the SCADA system often requires operator intervention to make decisions and tends to respond rather than predict. Above all, SCADA systems do not have a robust predictive ability, which in turn reduces its capability to find slight signs of potential failure before time, which sadly is absent in SCADA systems[7].

Limitations:

- The primary focus of SCADA systems is monitoring real-time conditions and typically do not analyze historical data or simulate future scenarios, which would reduce their ability to provide predictive insights.
- Some of the known vulnerabilities of centralised SCADA architecture include the problem of single points of failure, and may not be competent enough to handle modern distributed energy resources (DERs).
- SCADA systems are often dependent on human interpretation of the data they provide, which inevitably leads to delays in taking corrective actions and potential missed opportunities for proactive maintenance.

Phasor Measurement Units (PMUs) Phasor-Measurement Units (PMUs) are the time-synchronized measurements of electrical waves all over the power grid. It provides very accurate monitoring of the stability of the grid. The PMUs detect the disturbances that are in the grid, identify the weak points, and determine the overall performance of the grid. PMUs give real-time data but they do not predict failures for the future based on the pattern that has occurred[8].

Limitations:

- The high expenses associated with PMU installation limit their deployment, particularly in older or underfunded infrastructures.
- Despite the accuracy of PMUs in detecting disturbances, they do not offer predictive insights and therefore cannot prevent issues before they occur.
- The large volume of data generated by PMUs can overwhelm traditional data processing systems, resulting in inefficiencies in extracting actionable insights.

Periodic Manual Inspections and Maintenance Another traditional method of monitoring power grids is through periodic manual inspection and maintenance. Utility companies schedule routine inspections of major grid components,

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such as transformers, transmission lines, and substations. Field technicians evaluate the condition of these components and make necessary repairs. This method can identify any visible wear or damage but is time-consuming, labor-intensive, and prone to human error. Furthermore, the use of scheduled maintenance increases the chances of missing issues that develop between inspection periods[9].

Limitations:

- Manual inspections require significant time, labor, and financial resources.
- The infrequency of inspections could indicate that early signs of equipment deterioration can be missed, resulting in unforeseen failures.
- Human error during inspections could potentially lead to inaccurate assessments and increased operational risks.

Event-Driven Fault Detection Traditional power grids rely on event-driven fault detection systems, which detect alarms and initiate protective actions in the event of certain occurrences, like short circuits or overloads. Such systems use protective relays and circuit breakers to get to a faulty component by detecting anomalies. However, an event-driven system can only react after an event has happened and cannot prevent a disruption from happening. While these help reduce the impact of faults, they do not offer predictive capabilities or early warnings[10].

Limitations:

- These systems can only react to predefined thresholds or conditions, which could potentially result in overlooking early-stage issues and not triggering immediate alarms.
- Relying on event-driven systems can often result in prolonged downtime since operators work to restore grid operations after a fault has occurred.

2.2 Digital-Twin Technology in Smart-Cities

Digital-twin technology, that is based on virtual representations of physical assets and systems, is considered a transformational solution for managing complex urban environments[11]. The integration of digital twins within smart cities further improves infrastructure by providing real-time monitoring, simulation, and optimization.

Existing Implementations of Digital Twins Digital twins technology has been implemented with success in various smart city initiatives around the world in different infrastructure sectors[12]. Singapore and Dubai, for example, use digital twins to manage their urban planning and development. The Virtual Singapore project utilizes a detailed digital twin of the city to propagate urbanised planning, optimize resource allocation, and enhance public safety.

In the same vein, cities like Helsinki have utilized digital twins to enhance public transportation. The concept of developing real-time models of transport networks assists planners in analyzing traffic patterns and optimizing routes and service delivery[13].

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Applications of Digital-Twins in Power Systems Digital-twins in the power system are mainly advantageous in providing an improved monitoring and predictive maintenance approach and also enhancing the decision-making process[14].It is thus possible to respond more rapidly to abnormal conditions, hence decreasing the likelihood of an outage.

Application of digital-twins in power systems also extended towards predictive maintenance. Utilities can identify patterns of potential equipment failures through analysis of data from digital twins. This helps reduce unplanned downtime, prolong asset life, and save on maintenance costs. Through digital twins, the planning and optimization of energy resources can be properly improved. Utilities can plot different scenarios or conditions.This capability results in better decision-making regarding the resources that should be allocated.

Digital twin technology is, therefore, a key component in developing smart cities, offering innovative methods in urban infrastructure management[15],thus promising to transform the very way utilities operate in order to assure a more resilient and efficient energy grid.

2.3 Machine-Learning for Fault Detection

The integration of Machine-Learning (ML) techniques into power grid systems has significantly advanced the field of fault detection. Machine learning algorithms, based on vast amounts of operational data, can detect patterns and anomalies that may signify potential faults in grid infrastructure. Traditional fault detection methods, often based on threshold-based approaches, lack the adaptability and predictive power of machine learning[16]. Utilities are therefore looking at a myriad of machine learning approaches for the improvement of fault detection.

Previous Approaches Using Machine Learning in Grid Systems There are previous studies that have demonstrated the use of machine-learning for fault-detection in power systems[17]. Most popularly, supervised learning algorithms, including support-vector machines (SVM), decision trees, and random forests, are utilized. All these algorithms are trained from historical fault data to identify different types of anomalies that may lead to failures. For instance, [18] used random forests to analyze outage history data, and they received better accuracy in detecting faults than traditional methods. Similarly, deep models like neural networks have been used on power grid data to model intricate relationships present within the data for better fault detection related to equipment degradation.

Another approach is through unsupervised learning methods, namely, clustering algorithms and anomaly detection methods. Such methods do not necessarily make use of labeled data, hence particularly useful in identifying faults that are previously unseen[19].

Despite such promising results, these approaches have several challenges. Among them are data quality and data quantity, model-interpretability, and

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the ability of machine learning systems to interface with existing infrastructure for fault detection in power grids.

Genetic Algorithms and Their Role in Optimization and Prediction Genetic algorithms (GAs) are a strong optimization technique that has its inspiration in the principles of natural selection. In machine learning for fault detection, GAs can be applied for optimizing the parameters of the model, feature selection, and the overall architecture of the predictive models. The natural tendency of GAs to efficiently explore an extensive search space makes them highly suited to identifying optimal configurations in complex systems.

Genetic algorithms also serve another role in power systems: the optimization of machine learning models.For example, one possible application of GAs is to seek the best hyperparameters for machine learning models that would result in better predictive accuracy and robustness when performing fault detection tasks[20]. The hybrid GAs combined with machine learning improve the rate of fault detection as well as model efficiency to significant extents.

GAs may also be useful in determining which of the features are most contributing in predicting faults, thereby making significant power systems information about overwhelming volumes of data that might be produced[21]. Hence, the complexity of the model is reduced because it is based on a smaller number of more important features.

3 Methodology

3.1 Dataset

This study uses electrical grid stability simulated data to improve the proposed model's robustness in real-time fault detection and stability assessment within power grid systems. The dataset is specifically designed for the local stability analysis of a 4-node star system and contains over 60,000 labeled instances, representing a wide variety of grid conditions. It is multivariate, complete (no missing values), and serves as a crucial foundation for training and evaluating learning algorithms in predicting grid steadiness [22].

The variables included in the dataset offer valuable insights into the behavior of grid participants and their responses under varying conditions. Key columns include:

- **Reaction Times** $(\tau_1, \tau_2, \tau_3, \tau_4)$: Represent the reaction times of the four participants in response to fluctuating electricity prices. These are critical in understanding how the system might respond to disturbances that influence overall stability.
- **Mechanical Power** (p_1, p_2, p_3, p_4): Indicate the mechanical power generated (positive) or absorbed (negative) by each participant. Power dynamics play a vital role in maintaining a balanced and stable grid.

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- **Price Elasticity Coefficients** (g_1, g_2, g_3, g_4): Represent the price elasticity of each participant, helping estimate how responsive they are to price fluctuations and how that affects grid stability.
- **Stability Indicator** (*stab*): A numerical value measuring grid stability, with negative values indicating stable states and positive values indicating instability. This is the primary prediction target.
- **Categorical Stability Status** (*stabf*): Derived from the *stab* column, this categorical label classifies grid states as either "stable" or "unstable," aiding in classification tasks and model evaluation.

The dataset was generated using the methodology outlined in "Taming Instabilities in Power Grid Networks by Decentralized Control" (Benjamin Schafer, Carsten Garbow), which emphasizes decentralized control strategies to mitigate instabilities in power grid systems. This makes it highly aligned with our focus on digital twin-driven analysis and control.

Despite its usefulness, the dataset is simulated and represents an idealized version of a power grid, limited to a simplified 4-node star topology. This abstraction, while beneficial for initial algorithm development and theoretical analysis, does not fully capture the complexities, noise, and unpredictability of real-world power grid data. Real-world systems often involve higher node counts, nonlinear behaviors, communication delays, and missing or corrupted sensor data. These challenges can significantly affect model performance and generalizability. Therefore, while this dataset provides a strong baseline for experimentation and validation, future work must incorporate real-time, real-world datasets—potentially sourced from smart grid testbeds or utility partners—to ensure scalability, reliability, and practical applicability of the proposed digital twin approach.

This dataset will be used in model training to simulate a variety of scenarios and assess the impact of various parameters on grid stability. The large volume of labeled data enables the development of robust machine learning models, which can later be validated against real-time data generated by the digital twin of the power grid. This two-step approach helps bridge the gap between simulation and practical deployment, enhancing predictive accuracy and operational resilience for smarter, more stable grid infrastructure.

3.2 Digital-Twin Model

The digital-twin concept to be implemented for our power grid system is through the platform Azure Digital Twins. It is the platform from which holistic digital representations of physical environments can be created. The methodology, therefore, makes use of both the control plane and the data plane APIs to efficiently manage all the resources, models, and relationships in the Azure ecosystem.

Control Plane The control plane contains the resource manager APIs, which are employed to manage all the Azure resources that are associated with Azure Digital Twins. It includes those functionalities concerned with creating and deleting full instances of digital twins. It is also concerned with managing endpoints.

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Data Plane In contrast, it is the control plane that focuses on API requests related to operations on models, digital twins, relationships, and event routes within the Azure Digital Twins instance itself. The key components for the data plane are:

- **Event Routes:** Event routes are significant in the flow of digital twin data through the Azure Digital Twins graph and to endpoints to forward the data to downstream services for further processing.
- **Jobs:** The data plane supports the management of long-running jobs.
- **Models:** Custom definitions describe specific entities in an environment, such as generators, sensors, and consumers, and each type of entity has a corresponding model.
- **Query:** Querying capabilities will allow users to query the Azure Digital Twins graph regarding properties, models, and relationships.
- **Twins:** Finally, there are requests for managing the digital twins. These requests denote instances of a model reflecting specific entities within the environment. For example, in a single model of the Generator, multiple digital twins can be there, namely, Generator A, Generator B, and Generator C.

This design we would implement using the Azure Digital Twins Command Line Interface (CLI) to manage user roles. For example, we add a role assignment for a "SAZURE USER" user assigned to the "Azure Digital Twins Data Owner" role in the instance of the "powergrid" Digital Twin of the resource group "azure-digital-twins-training". This would be the role assignment that would ensure that the users, once assigned, are enabled with the right permissions to do most things within the digital twin environment.Also, User Access Control (UAC) settings on this storage account are enforced to limit access to only twin owners; they can read and write, upload, or execute data in the account.

By integrating all these components and methodologies into our digital twin system, it should become a powerful tool for realtime monitoring and speculative analysis of the power-grid.

3.3 Machine Learning Workflow

Our workflow is to make our model robust, scalable, and optimized for use in real-time applications. This process involves several very crucial stages: data preprocessing, feature extraction, model training, and finally, the deployment on Microsoft Azure.

Model Training and Deployment on Microsoft Azure We used an AutoML framework called TPOT (Tree-based Pipeline Optimization Tool) that aims at designing machine learning pipelines in a rather automatic way, through automated optimization. TPOT will discover the best-performing pipeline by searching over numerous configurations of models, preprocessing steps, and hyperparameters without much need for a human.GAs encode possible solutions as

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chromosomes and itera- tively evolve those solutions to maximize a predefined fitness function.

The TPOT optimization process involves several key parameters:

– **Generations:** We set the number of generations to 5, meaning TPOT iteratively improves the population of pipelines over five cycles and enhances their performance at each stage.
– **Population Size:** In each generation, it evaluates a diverse set of 20 pipelines. That means that during optimization, there is a large variety of models considered.
– **Cross-Validation (cv=5):** TPOT uses 5-fold cross-validation for evaluation, which ensures consistency and reliability in the performance of pipelines over different subsets of the training data.

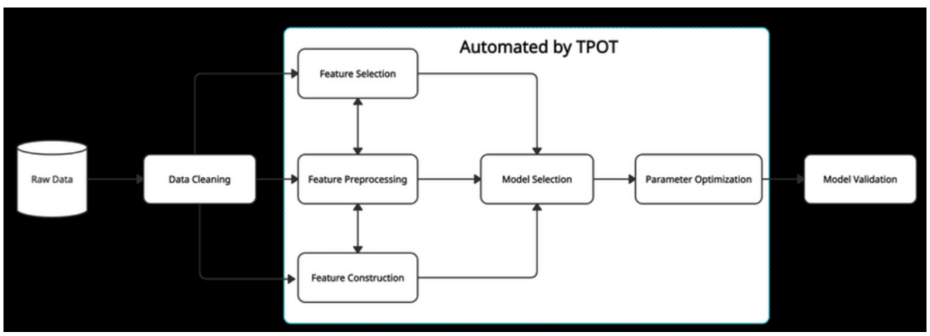

Fig. 1. Model Architecture

Cloud-Based Processing and Scaling We then deploy the optimal model on Microsoft Azure, where the power of cloud-based processing and scaling can be unleashed. The Azure platform offers necessary resources for handling large amounts of data and real-time computations, which is indispensable for our application's necessities. Utilizing Azure's robust infrastructure ensures that the model can work efficiently regardless of the loads and varying conditions, thereby ensuring fault detection in the power grid system in a timely and proactive manner.

Fig.2 shows a fully realized project of a complete Digital Twin solution that will build and deploy on the asset site. Data collection, preprocessing, feature engineering, model training, and real-time fault detection are incorporated within the architecture. Deployed on the Azure cloud platform, integration to multiple assets and systems in real-time, provides this capability for predictive maintenance.

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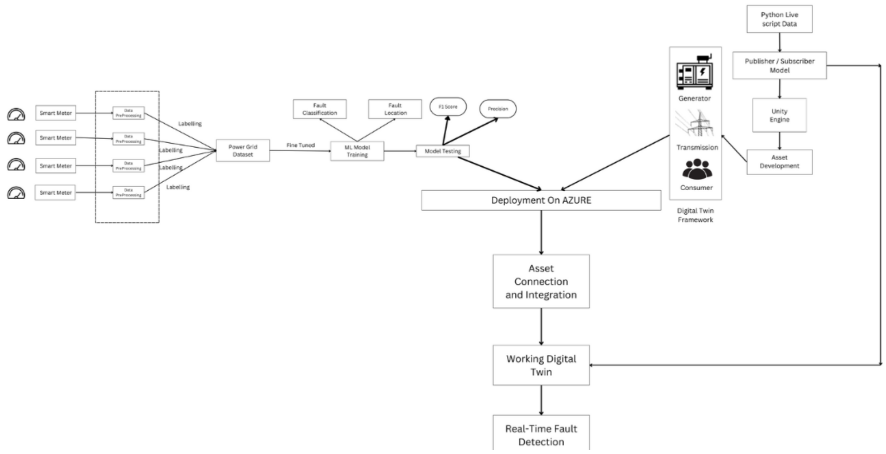

Fig. 2. High Level Workflow

4 Results and Discussion

4.1 Benefits of Graph Digital-Twin in Smart-Cities

Implementing a graph digital-twin for the smart power grid system introduces a more advanced approach to monitoring and managing city-wide infrastructure. This setup is crucial for managing the complexity of urban energy systems and supports the integration of the power grid with other smart city infrastructures, such as transportation and emergency response systems.

Graph digital twins enhance resilience by offering a real-time understanding of the relationships between different components in the power grid. In the event of a fault, the graph structure enables the system to quickly identify impacted nodes and reroute power, maintaining supply to critical services. Additionally, by simulating various fault conditions, operators can proactively strengthen the network's resilience. The digital twin approach thus enables a shift from reactive to proactive grid management, helping to prevent issues before they escalate.

Fig. 3 illustrates the final graph digital twin of a smart power grid system. Each node in the graph represents a specific component of the power grid, including city plants, delivery substations, domestic consumers, farm consumers, industrial consumers, and various energy sources like industrial plants, solar plants, and wind plants. The edges between the nodes indicate power lines that connect these components, showing the flow of electricity across the system. This visual setup helps monitor and manage the interactions between different elements of the power grid, enhancing stability and efficiency.

4.2 Fault Detection Performance

The fault detection capabilities of our model, optimized using TPOT, were evaluated with several key metrics, which include among others precision, recall,

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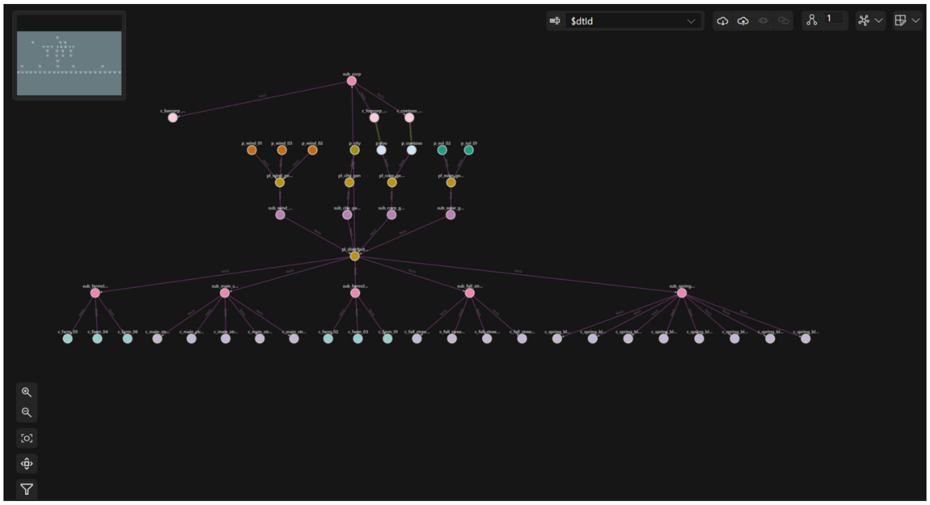

Fig. 3. Graph Digital Twin of Smart Power Grid implemented on Microsoft Azure

F1-score, and accuracy. These metrics help predict the model's performance in accurately detecting faults within the power grid. The model achieved high precision, ensuring that instances identified as faulty are indeed faulty, thus minimizing false positives. High recall values demonstrate the model's effectiveness in identifying nearly all actual faults, ensuring that potential issues are caught before escalation.

The F1-score produces a balanced metric, integrating precision and recall to reflect the model's robustness across different fault scenarios. A high F1-score confirms that the model performs consistently well, even in complex situations. Additionally, the model attained an overall accuracy of 98.6%, indicating its high reliability in classifying instances within the dataset accurately. When compared to baseline models, this optimized approach demonstrated significant improvements in fault detection accuracy, supporting the utility of graph digital twins combined with advanced machine learning techniques for effective fault management in smart power grids. The confusion-matrix displayed in Fig. 4 provides an in-depth evaluation of the model's fault detection performance, illustrating how well the model classifies stable and unstable states within the power grid system. Here's a breakdown of the matrix components:

1. **True Positives (TP)**: There are 1,260 instances in the bottom-right cell where the model correctly identified faults (labeled as "1") when they actually occurred. This reflects the model's ability to detect faulty conditions accurately.

2. **True Negatives (TN)**: The top-left cell shows 1,257 instances where the model accurately classified the stable state (labeled as "0"). These are cases where no faults occurred, and the model correctly identified them as such.

3. **False Positives (FP)**: In the top-right cell, there are 13 instances where the model incorrectly classified a stable condition as a fault. This represents the

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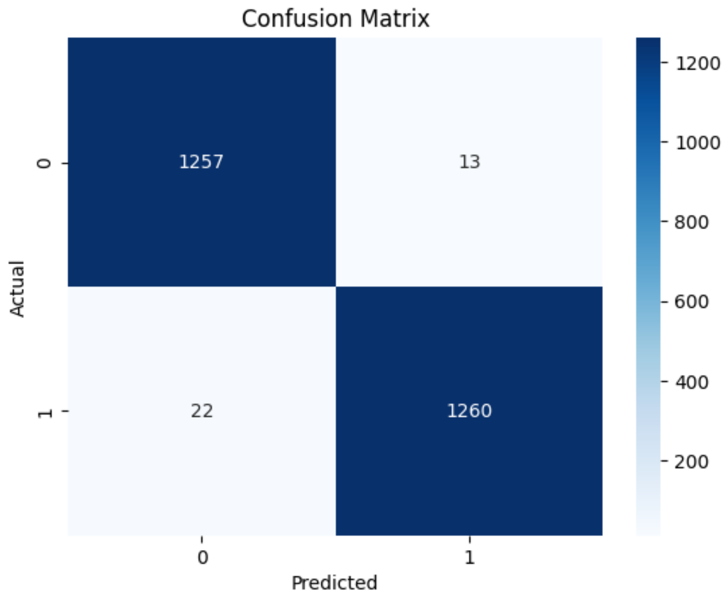

Fig. 4. Confusion Matrix of TPOT Model

cases where the model generated a false alarm, identifying a fault when there was none.

4. **False Negatives (FN)**: The bottom-left cell shows 22 instances where the model failed to detect an actual fault, misclassifying it as a stable condition. These instances represent missed fault detections, which could potentially impact grid stability if faults go undetected.

The low false positive rate suggests minimal disruption from unnecessary alarms, while the low false negative rate indicates reliability in capturing most actual faults, supporting the model's application in real-time fault detection and grid stability enhancement.

TPOT Performance Analysis As evidenced by the classifier performance summary in Fig. 5, TPOT demonstrates superior performance among all evaluated classifiers. With a baseline accuracy of 98.3 percent and a tuned accuracy of 98.6 percent, TPOT achieved the highest performance metrics in the comparative analysis. The 0.3 percent improvement through optimization, while modest, represents significant enhancement given the already exceptional baseline performance. In comparison, other classical machine learning approaches showed lower performance levels: Support Vector Classifier achieved 97.3 percent after tuning with a 0.6 percent improvement, Gradient Boosting Classifier reached 95.5 percent with a 1.5 percent improvement, Random Forest Classifier attained 92.4 percent with a 0.4 percent increase, and K-Nearest Neighbors Classifier

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achieved 90.4 percent with a 1.2 percent improvement. The substantial performance gap between TPOT and simpler models like Logistic Regression, which achieved 81.5 percent accuracy, underscores TPOT's effectiveness in automated machine learning optimization. TPOT's superior performance can be attributed to its automated pipeline optimization capabilities, which include comprehensive feature preprocessing, model selection, and hyperparameter tuning. The high baseline accuracy demonstrates TPOT's capability to establish strong initial configurations without extensive manual tuning, making it particularly suitable for immediate deployment in fault detection systems.All the preceding classical classifier performance were computed on the same azure instance as the GA algorithm for comparable results.

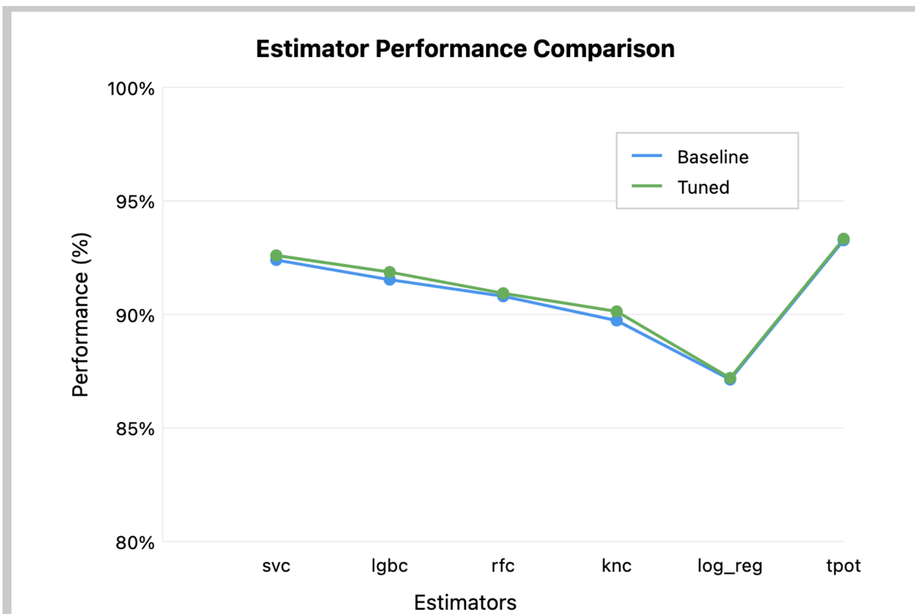

Fig. 5. Estimator Performance Comparison

5 Conclusion and Future Work

We propose a new approach in this research for the improvement of fault detection and stability of power grids by graph digital twins and advanced machine learning techniques. A full-scale digital twin of the power grid was developed with the use of Microsoft Azure IoT TwinMaker to enable real-time monitoring and predictive analysis. Substantive accuracy improvements in the detection of faults were also derived through the deployment of the classifier models optimized using TPOT and cloud-based processing. These improvements can facilitate the

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enhancement of the reliability as well as efficiency of a power grid system. Such research, therefore, serves as a basis for identifying and establishing the potential benefits and application areas of using a combination of digital-twin technology with machine-learning in a smart city context for the proper handling of challenges in its management of power infrastructure.

More lines of future work open up in the subsequent avenues. More and more components of the smart grid can be integrated into the digital twin model. In particular, renewable energy sources and storage systems might be included to give a holistic view of the dynamics of the grid. Future research can focus on the inclusion of realtime data feeds from IoT devices that might eventually enhance the response capabilities of the fault detection algorithms.

Another important aspect of future work will be the validation of the proposed models using real-world operational data. This includes exploring potential collaborations with utility companies, smart grid pilot projects, or national power system research initiatives to gain access to authentic grid data.Such validation will ensure the proposed model can generalize beyond simulated environments and operate reliably under real-world grid conditions.

While our current work demonstrates enhanced fault detection capabilities, ensuring overall grid stability—especially with the integration of intermittent renewable sources—remains a complex challenge.To address this, future extensions of our model will incorporate dynamic load balancing algorithms and predictive analytics that consider fluctuations in renewable input. Coupling digital twins with energy storage modeling and real-time demand-response mechanisms will allow for better simulation of these scenarios, supporting a more stable and adaptive grid in the presence of renewable generation.

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