Spatiotemporal Multiplex Network Model for Predicting Forced Outage Severity in Distribution Grids

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Abstract. Weather-related power disruptions present significant challenges to public infrastructure, societal well-being, and the distribution grid. Predicting outage durations in distribution grids is another challenge compared to transmission line outage durations due to distribution networks' complexity and finer granularity. While forecasting forced power outages is crucial, accurately estimating their duration is essential for timely response and mitigation measures. This study introduces the Spatiotemporal Multiplex Network (SMN-WVF), a methodology designed to predict power outage durations across varying lead times, tackling the difficulties posed by small, high-complexity spaces within distribution grids. SMN-WVF employs multiplex networks that incorporate multi-modal data across both time and space, including layers such as power outages, weather conditions, weather forecasts, vegetation, and distances between substations. We demonstrate the importance of incorporating additional layers of data sources as they are shown to help the model's predictions through gradual improvement in the macro F1 score performance.

Keywords: Forced power outage · multiplex network · spatiotemporal prediction

1 Introduction

Forced power outages (further referred to as "outages") have a considerable impact on both the economy and the lives of residents in affected areas. The causes of such power outages can be broadly divided into four primary categories: emerging threats, accidental incidents, malicious activities, and natural events

L. Iliadis et al. (Eds.): EANN 2025, CCIS 2582, pp. 165–178, 2025.
https://doi.org/10.1007/978-3-031-96199-1_13

[10]. Severe outages, particularly those in rural regions, can last for extended periods and require significant restoration time [30]. Furthermore, power system operations are typically classified into four distinct states: normal operation, alert, emergency, and extreme [13]. Previous research studied the power outage problem statistically, employing techniques such as quantile regression forests and Bayesian additive regression tree models [31]. In contrast, recent advancements in machine learning have shifted towards predictive models that utilize machine learning techniques to enhance the accuracy of power outage predictions and identify their causes [19]. Previous research also employed graph-based models to predict power outages [11,25]. However, these studies did not leverage multiplex networks to improve predictions; instead, they were limited to using single-layer input.

Predicting power outages is essential, but predicting their duration is crucial to efficient response and mitigation actions. Statistical methods [21] and machine learning models [12] have been applied to predict the duration of power outages. However, researchers have yet to fully explore the potential of multiplex networks that integrate data from multiple sources. In our previous study [1], multiplex graphs demonstrated their effectiveness in predicting the occurrence of power outages. Based on this, our follow-up study [2] successfully used multiplex graphs to predict the duration of power outages, outperforming alternative approaches. However, neither analysis addressed the prediction of the duration of outages for the distribution grid. To address this limitation, our current study introduces SMN-WVF, a Spatiotemporal Multiplex Network model designed to predict the duration of power outages while extending prediction time intervals demonstrating a use case of a utility in Texas, U.S.A. SMN-WVF integrates data from multiple sources, including weather, forecasts, and vegetation, collected across space and time. By providing earlier warnings of outage risks, this model aims at enhancing the efficiency of outage management and improving response efforts. The key contributions of this paper are:

1. Establishing a foundational framework for improving spatiotemporal classification by incorporating multi-modal data to tackle the challenges of missing weather recordings effectively.
2. Introducing Spatiotemporal Multiplex Network methodology to predict power outage durations by employing the multi-modal approach.
3. Applying the new approach to estimate outage severity (duration) in the distribution grid by providing insights distinct from those focused on transmission line outages.

2 Related Work

Extreme weather events like severe storms (rain, snow, wind) and other catastrophic natural disasters (earthquakes, wildfires, hurricanes) can cause power outages. To improve the planning of power restoration efforts, accurately predicting the duration of power outages early is crucial for utility companies.

Various statistical approaches have been employed to estimate outage duration, including accelerated failure time regression, Cox proportional hazards regression, Bayesian additive regression trees, regression trees, and multivariate adaptive regression splines [21]. Some studies integrate statistical methods with geographic information systems (GIS) to analyze urban distribution systems affected by winter storms. For example, GIS tools were used to map repair crew data and examine the duration of outages during such events [26]. Similarly, researchers have applied Accelerated Failure Time (AFT) and Cox Proportional Hazard (CPH) models to estimate storm-induced power outage durations [18]. In another example, daily Night Time Lights (NTL) imagery data has been utilized to assess the duration of outages in Puerto Rico [7]. In addition, studies indicate that socioeconomic factors play a significant role in determining the outage duration [20]. Recently, the focus has shifted toward leveraging machine learning models to predict the duration of power outages more accurately. For instance, Random Forest-based models have been used to forecast the duration of hurricane-related outages, incorporating variables such as wind speed and duration [22]. Furthermore, machine learning techniques such as Extra Trees (ET), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Random Forest (RF), Gradient Boosting Regression (GBR), and Decision Tree (DT) have been applied to predict outages durations during typhoon disasters [15].

Weather data plays a crucial role in predicting power outages [9]. However, severe weather conditions often result in many missing values in weather recordings, which present challenges for predictive modeling. Our research integrates weather data with multi-modal learning techniques to address this challenge. Given the challenges of missing data, multi-modal learning techniques offer a promising solution by improving predictive accuracy [1,5,8,24]. In particular, we explore multiplex networks' impact in predicting the power outage duration at the distribution grid level. The network structure is crucial for capturing complex interdependencies between different data sources, thus improving the accuracy and robustness of the predictions [3,4]. This study introduces a novel approach that leverages multiplex network representations to predict the power outage duration for severe weather cases. Specifically, we evaluate the benefits of using a Spatiotemporal Multiplex Network that integrates data from multiple key sources: power outages, weather observations, weather forecasts, vegetation, and distance between the substations.

3 Methodology

This study investigates the effectiveness of the proposed Spatiotemporal Multiplex Network (SMN-WVF) model, which combines multiplex networks and multi-modal data, in improving the prediction of power outage duration. The SMN-WVF model estimates the duration of the predicted outages by predicting their duration. Figure 1 illustrates the pipeline of the proposed approach to building the Spatiotemporal Multiplex Network model that includes information captured at five layers from different sources. The research is divided into three phases: (1) data collection, (2) construction of a spatiotemporal graph, and (3) development of the model that predicts the duration of expected outages. Detailed descriptions of each component of this framework are provided in the following subsections.

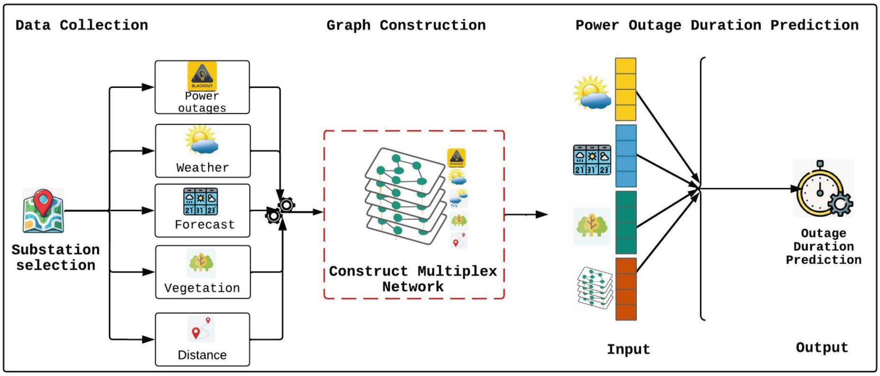

Fig. 1. The architecture of the Spatiotemporal Multiplex Network (SMN-WVF) for multi-modal prediction of power outage duration.

3.1 Data Collection

In our previous research [1], we demonstrated the advantages of integrating data from diverse sources to improve the prediction of the duration of power outages. To achieve this, we identify and gather key factors that influence the power outage duration. These factors include power outage records, weather conditions, forecasts, and vegetation data. This subsection outlines the data collection process.

1. **Power outages data:** We utilize a historical outage dataset obtained from a Texas utility company, which details when and where outages occurred from January 2018 to December 2023. To effectively use this dataset, it is crucial to correlate each outage occurrence with the corresponding substation. The dataset contains outage start and end times, outage cause codes, the nearest substation, failed equipment IDs, and repair crew comments. We employ the equipment ID and nearest substation fields to map each outage to its respective substation. Historical outage data are recorded in the local time zone. However, since most public datasets use UTC for timestamps, we converted the outage timestamps from the local time zone to UTC and linked the events with the appropriate substation ID. Our study utilizes six years of historical outage data during which the reported power outages reveal a total of 109,366, with an average duration of 101.08 min.

2. **Weather data:** Between January 2018 and December 2023, we collected weather data from Automated Surface Observing Systems (ASOS) [6] The ASOS database includes hourly information retrieved from the ground weather station sensors, as well as data about the station's location, sky conditions, obstructions to vision, pressure, ambient temperature, wind, and precipitation accumulation for point locations. We collected $8,425,383$ observations from ASOS weather stations. However, the substations are not connected to an ASOS weather station; therefore, we map each substation to the closed ASOS station using latitude and longitude. We use the Haversine formula to calculate the distance between the substation and the ASOS stations [27].

3. **Weather forecast data:** The ASOS database does not include weather forecast data. To obtain this information, we use the OpenMeteo API, providing open-source weather forecasts from national weather services [23]. Open-Meteo offers weather models with a resolution of 11 km and regional models with up to 1.5 km resolution. The database provides hourly data on various weather parameters, including temperature, relative humidity, dew point, precipitation, wind speed, and wind direction. By providing the latitudes and longitudes of the substations, we collect forecast data for each substation based on its proximity to the nearest weather model. Our focus has been on analyzing forecast information during the mentioned power outages resulting in the collection of $3,575,712$ observations.

4. **Vegetation:** The landscape of a geographic location is a critical factor in predicting power outages. To account for this, we collected vegetation data from the Ecological Mapping Systems (EMS), which offers a comprehensive land cover summary for Texas. The EMS data has a spatial resolution of 10 meters per map [29].

3.2 Data Preprocessing

To assess the impact of the spatial-temporal multiplex network on predicting the duration of power outages, we use individual and a combination of modalities. These features are gathered from various sources, including weather, forecasts, vegetation, and distance between the substations. Due to the wide range of features, our feature selection eliminates irrelevant information and identifies the most relevant features that enhance the model's performance. In this process, the weather dataset includes the following features: weather station location, sky conditions, visual obstructions, pressure, ambient temperature, wind, and precipitation. We calculate the maximum, minimum, mean, and standard deviation for each selected weather feature per day and time window for each substation. The forecast dataset includes the following features: temperature, relative humidity, dew point, precipitation, wind speed, and wind direction. We also calculate the maximum, minimum, mean, and standard deviation for each selected weather feature per day and time window for each substation.

3.3 Spatiotemporal Multiplex Network Creation

Consider G as a Spatiotemporal Multiplex Network represented by $G = (V, E, L, T)$, where $V = \{v_1, v_2, ., v_n\}$ denotes the set of vertices corresponding to substations, $E = \{e_1, e_2, ., e_m\}$ represents the set of edges, $L = \{l_1, l_2, l_3, l_4, l_5\}$ is the set of layers, and $T = \{t_1, t_2, ., t_k\}$ is the set of time steps. The network comprises five distinct layers: $l1$ corresponds to the power outage layer, $l2$ is the weather layer, $l3$ represents the forecast layer, $l4$ is the vegetation layer, and $l5$ refers to the distance layer. In the multiplex network, all vertices across different layers represent the same entities but reflect various types of interactions among the vertices. Specifically, the vertices V represent substations. The connections between the vertices illustrate different types of interactions, with each edge e assigned a weight that is a real number greater than or equal to 1. This weight indicates the strength of the connection between vertices (v, u) in the i^{th} layer. The set of edges E in each layer l_i signifies a different type of relationship among the vertices V, as explained below:

1. **Power outage layer (E_{l_1})**: If a power outage is reported in both substations on the same date and time window, the vertices (u_{l_1}, v_{l_1}) are connected. The edge weight ω represents the shared power outages between these substations.
2. **Weather layer (E_{l_2})**: We assume that power outages are closely linked to weather conditions. As a result, vertices (u_{l_2}, v_{l_2}) are connected if they reveal similar weather properties. To quantify this similarity, we use Euclidean distance. By measuring the Euclidean distance between the weather features, we can determine the closeness of the weather conditions between the substations.
3. **Forecast layer (E_{l_3})**: Vertices (u_{l_3}, v_{l_3}) are connected if they share similar weather properties, since weather conditions have a significant impact on power outages. In this context, we use Euclidean distance to measure the similarity between the weather attributes of the two vertices.
4. **Vegetation layer (E_{l_4})**: We connect two vertices (u_{l_4}, v_{l_4}) (substations) if they exhibit similar vegetation properties. To assess this similarity, we compute the Euclidean distance between their corresponding vegetation features. This method helps illustrate the potential influence of vegetation on power outages, as comparable vegetation patterns may lead to similar outage behaviors.
5. **Distance layer (E_{l_5})**: Two vertices (u_{l_5}, v_{l_5}) (substations) are connected based on their spatial distance. To quantify this distance, we use the Euclidean distance. This measure helps capture the physical proximity between substations, which is essential as the spatial closeness of substations may influence the likelihood of shared power outage events or other related factors.

This graph serves as input for the Spatiotemporal Multiplex Network (SMN-WVF) model. At the end of each day, a new snapshot of the multiplex graph is generated for each time window, timestamped with that day's data, to capture the interdependencies among substations. We train the model using these daily snapshots as input, generating embeddings for the substation nodes through the proposed method, which is detailed in the following subsection. The aim is to predict the duration of a power outage at a substation and connected feeders.

3.4 Proposed Model: Spatiotemporal Multiplex Network (SMN-WVF)

This study investigates the potential of the Spatiotemporal Multiplex Network (SMN-WVF) combined with multi-modal data to improve the prediction of disruption severity expressed as the outage duration. Initially, a historical outage dataset from a Texas utility company is utilized, where outage frequency varies across different substations. Each data point is marked as 1 if a power outage occurs in a specific substation during a specific time. Next, the outages are categorized into three groups to predict outage duration, as detailed in Table 1. The model aims to predict the duration of a power outage once it has been identified. It classifies outages into predefined duration categories, as shown in Table 1. This classification aids in estimating the duration of each outage, thereby helping to understand disruption severity and improve planning and response. To enhance predictions, the model employs a modified version of Node2Vec [14] to generate substation node embeddings that incorporate multiple graph layers. We combine the structured data with unstructured data (multiplex model embeddings), creating a unified input dataset for predicting outage duration. This combined input is then processed through a Bidirectional Long Short-Term Memory (BiLSTM) network with eight layers.

Table 1. Distribution of power outage durations across three classes of duration from January 2018 to December 2023.

Class	Duration	Percentage
Class 1	Less than 1 hour	35.1%
Class 2	1 to 3 h	34.9%
Class 3	Greater than 3 h	29.9%

4 Experimental Setup

This study examines whether the multiplex network combined with a multi-modal data approach can enhance the early classification of disruption severity (duration) into one of three categories, ranging from short to very long durations. The study covers six years of historical outage data from January 1, 2018, to December 31, 2023. The training data spans from January 1, 2018, to December

31, 2021, while the testing data covers January 1, 2022, to December 31, 2023. We compare the performance of the Spatiotemporal Multiplex Network model using weather, vegetation, and forecast features. The model is optimized using the Adam optimizer [16], employing a batch size 32 and a learning rate 0.0005. The model is trained with sparse categorical cross-entropy loss, which is used for multiclass classification to improve its ability to predict outage durations across the specified classes.

The study uses a supervised machine-learning approach to predict the duration of disruptions caused by power outages. Since our classification task involves three distinct classes, we employ macro-averaging, which gives equal importance to all classes, regardless of their frequency in the dataset. Specifically, we calculate macro precision and macro recall to measure the model's false positives and false negatives rates. We evaluate the model's overall performance using the macro F1 scores for each class. Here, C denotes the total number of classes, and the macro F1 score is defined as:

$$\text{Macro F1} = \frac{1}{C}\sum_{i=1}^{C} 2 \cdot \frac{\text{precision}_i \cdot \text{recall}_i}{\text{precision}_i + \text{recall}_i} \tag{1}$$

5 Spatiotemporal Multiplex Network Analysis

This section presents the results of the topological structure analysis conducted on the constructed weighted multiplex networks. To gain a comprehensive understanding of these networks, we examine various centrality measures, including Degree Centrality (DC), Closeness Centrality (CC), Eigenvector Centrality (EC), Square Clustering (SCF), and the Clustering Coefficient (CF), to further explore the network's structural properties. Here, we report the average values of all these measures.

Table 2. Multiplex network topological structure. Here L = number of layer, V = number of nodes, E = number of total edges, $coupling\, E$ = number of coupling edges, $avg(DC)$ = average degree centrality, $avg(CC)$ = average closeness centrality, $avg(EC)$ = average eigenvector centrality, $avg(SCF)$ = average square clustering, $avg(CF)$ = average clustering coefficient.

L	V	E	$coupling\, E$	$avg(DC)$	$avg(CC)$	$avg(EC)$	$avg(SCF)$	$avg(CF)$
5	430	$14.9M$	$1,720$	161.57	0.484	0.0169	0.482	0.898

Degree Centrality (DC) measures the connectivity of a node based on the number of edges connected to it, which provides insight into the node's significance and potential role as a hub in the network. Nodes with a higher degree of centrality are considered more central, as they are more connected than others. It is calculated as follows:

$$C_D(G) = \frac{\sum_{i=1}^{|V|}[C_D(v*) - C_D(v_i)]}{|V|^2 - 3\,V| + 2}, \tag{2}$$

where v represents a vertex in the graph G. On the other hand, Closeness Centrality (CC) reflects how close a node is to all other nodes within the network. A node with the shortest overall distance to other nodes has a high Closeness Centrality, making it a key candidate for spreading information. We calculate CC as:

$$C(v) = \frac{N-1}{\sum_u d(u,v)}, \tag{3}$$

where N refers to the total number of nodes in the graph, and $d(u,v)$ represents the distance between the vertices u and v. Eigenvector Centrality (EC) considers the significance of a node's neighbors. In addition, it determines a node's centrality based on the centralities of its neighboring nodes. EC is shown in the following equation as follows:

$$x_v = \frac{1}{\lambda}\sum_{u\in M(v)} x_u = \frac{1}{\lambda}\sum_{u\in G} a_{v,u}x_u, \tag{4}$$

where $A = (a_{v,u})$ is the adjacency matrix of the graph G, $M(v)$ denotes the set of neighbors of node v, and λ is a constant. The Clustering Coefficient (CF) reflects the average number of edges between nodes within each node's neighborhood. Following is the calculation of the Clustering Coefficient:

$$\bar{C} = \frac{1}{n}\sum_{i=1}^{n} C_i, \tag{5}$$

Finally, Square Clustering (SCF) extends the traditional Clustering Coefficient by focusing on the likelihood that two neighboring nodes share a common neighbor that is not part of the original node's neighbors, thus forming a square-shaped connection [17]. It can be calculated as:

$$C(v) = \frac{\sum_{u=1}^{k_v}\sum_{w=u+1}^{k_v} q_v(u,w)}{\sum_{u=1}^{k_v}\sum_{w=u+1}^{k_v}[a_v(u,w) + q_v(u,w)]}, \tag{6}$$

where $q_v(u,w)$ denotes the number of common neighbors shared by u and w, excluding v. Table 2 presents a detailed network analysis. The graph consists of 430 nodes and $14,902,735$ edges. A key characteristic of a multiplex network is the presence of coupled edges ($coupling\,E$), which represent the transitions of nodes between neighboring layers [28]. Networks with more coupled edges are generally denser and exhibit richer connectivity than those with few or no coupled edges. In this network, there are $1,720$ coupling edges. The graph contains 86 unique nodes, with an average degree centrality of 161.57, indicating a well-connected network. The average closeness centrality is 0.484, reflecting the average proximity between nodes in the graph. Additionally, the average eigenvector centrality is 0.0169, which suggests that nodes with higher centrality are spread out in the network. The average square clustering is 0.482, indicating moderate clustering. The clustering coefficient is 0.898, signifying a highly interconnected overall structure.

6 Results and Discussion

The results for different evaluation metrics of the proposed Spatiotemporal Multiplex Network (SMN-WVF) model using weather, vegetation, and forecast features are shown in Table 3. We emphasize the effectiveness of incorporating multi-modal learning to improve predictive performance. Each variant of the SMN model explores the contribution of specific feature combinations to the overall results. SMN-WV is the proposed model that incorporates both weather and vegetation data. In addition, SMN-WF employs both weather and forecast data. Lastly, the SMN-WVF model combines weather, vegetation, and forecast data for its predictions.

Table 3. Comparison of macro precision, macro recall, and macro F1 score of the proposed Spatiotemporal Multiplex Network (SMN-WVF) model using weather (W), vegetation (V), forecast (F) features, and the Spatiotemporal Multiplex Network. The outage duration is classified into three classes, as detailed in Table 1.

Modality	Macro precision	Macro recall	Macro F1 Score
SMN-WF	0.42	0.40	0.41
SMN-WV	0.43	**0.42**	0.42
SMN-WVF	**0.45**	0.41	**0.43**

We can observe that incorporating weather and vegetation (SMN-WV) yields slightly better results, with a macro F1 score of 0.42 compared to weather and forecast (SMN-WF). This suggests that vegetation can play a critical role in power outages, particularly due to incidents such as trees falling onto or touching overhead lines due to wind impacts, which are significant causes of power faults. Furthermore, the SMN-WVF model improves prediction performance by up to 2% compared to alternative models. The SMN-WVF model demonstrates strong predictive capability, consistently outperforming alternative models despite the inherent challenges of outage prediction in a small distribution grid area. Notably, it achieves a macro F1 score of 0.43. Unlike transmission networks, where outages often follow large-scale, high-impact events, distribution grids present a significantly harder prediction task due to their localized nature, smaller coverage area, and complex outage drivers. Outage durations in distribution grids are influenced by a mix of highly complex localized factors, and relying significantly on regional weather data makes accurate outage prediction

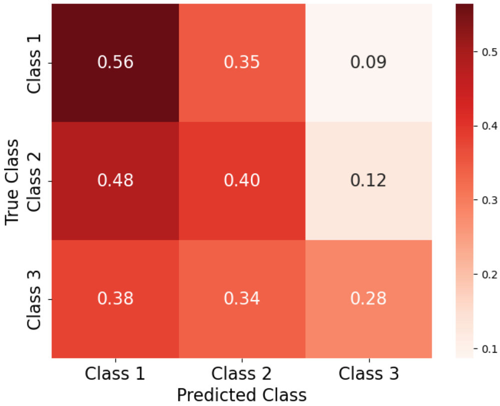

Fig. 2. The normalized confusion matrix of the SMN-WVF model, which utilizes weather, vegetation, and forecast features along with the Spatiotemporal Multiplex Network, demonstrates its predictions for outage durations. The classification is defined as follows: Class 1 represents duration from 30 min to 3 h, Class 2 represents duration from 3 and 6 h, and Class 3 represents duration greater than 6 h.

even more difficult. The multi-modal approach, integrating weather, vegetation, and forecast features, helps mitigate these challenges by capturing additional contextual information beyond weather and forecast features alone. Given the small-scale nature of the study area, even achieving a moderate macro F1 score indicates that the model is successfully generalizing across different outage conditions rather than overfitting to frequent outage patterns.

Table 4. Comparison of precision, recall, and F1 score of every class using SMN-WVF model.

Class	Precision	Recall	F1 Score
Class 1	0.44	0.56	0.49
Class 2	0.37	0.40	0.38
Class 3	0.52	0.28	0.37

We evaluate the performance of the SMN-WVF model using a confusion matrix. Figure 2 provides a breakdown of the correct and incorrect predictions. The classification categories are defined as follows: Class 1 represents the duration from 30 min to 3 h, Class 2 represents the duration from 3 and 6 h, and Class 3 represents the duration greater than 6 h. We further analyze the predictions for each class. Table 4 details the results of the SMN-WVF model per class. The results show that Class 1 achieves the highest recall (0.56) and a moderate F1 score (0.49), indicating relatively better identification of these instances. Class 2 has the lowest precision (0.37) and recall (0.40), resulting in an F1 score of 0.38.

Class 3 exhibits the highest precision (0.52) but suffers from low recall (0.28), leading to a reduced F1 score of 0.37. These results highlight the model's tendency to favor precision over recall, particularly in Class 3, potentially leading to underestimation of certain outage durations.

The second experiment assesses the effectiveness of the SMN model using different SMN-WVF models in making predictions at earlier stages. In the context of power systems, earlier predictions yield greater benefits. Table 5 illustrates the macro F1 score achieved for the early prediction scenarios. This score reflects the ability of the SMN model to detect outages in advance. We can observe that the macro F1 score remains stable and yields similar results as the prediction time approaches the outage event.

Table 5. Performance of the proposed Spatiotemporal Multiplex Network (SMN-WVF) model using macro precision, macro recall, and macro F1 score for early outage detection, evaluated across a three-class problem formulation, as detailed in Table 1.

Lead time of power outage	Macro precision	Macro recall	Macro F1 Score
0 h	0.45	0.41	0.43
6 h	0.43	0.41	0.42

7 Conclusion

Power outages pose serious threats to residential, commercial, and industrial customers, as well as transportation, healthcare, communication, and other essential services. Making effective predictions of their occurrences and duration is paramount for strategic outage mitigation planning. This study introduces the Spatiotemporal Multiplex Network with Weather-Vegetation-Forecast (SMN-WVF) method, a novel approach designed to improve power outage duration predictions. By integrating multi-modal data and network structures, our model evaluates outage durations across different time horizons, offering insights with various lead times. Even with the challenges of geographically confined space and the difficulties of predicting the outage duration, particularly in distribution grids–which are more intricate and finer-grained than transmission line outages- our SMN-WVF method demonstrates practical results. Our multiplex network comprises multiple layers, including power outages, weather conditions, weather forecasts, vegetation properties, and substation connectivity, allowing us to capture both temporal and spatial dependencies in the outage process. We rigorously assess whether our innovative network approach enhances predictive accuracy compared to simple weather data inputs. Our method achieves a macro F1 score of 0.42, underscoring both the difficulty of the task and the need for further advancements in outage duration predictions. We observe that integrating vegetation and forecast enhances performance by providing additional context beyond weather conditions alone. These findings highlight the importance of incorporating diverse data sources to improve outage duration predictions. Future work will focus on refining spatial feature representation and expanding alternative data sources. Also, it is worth exploring model performance while looking into node representations as a substation grouping. Looking ahead, we will evaluate our model's performance across diverse geographic regions and explore its efficacy with extended prediction intervals.

Acknowledgments. This work was funded by the National Science Foundation Award # 2125985.

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