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RESEARCH ARTICLE

Unveiling Weather-Induced Blackouts: A Ten-Year Analysis With Deep Learning-Driven Power Resilience Enhancement

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ABSTRACT When a rainy day affects the power grid, instead of enjoying the weather, many consumers face unplanned blackouts worldwide. Approximately 80% of blackouts in the US are weather-induced power outages. Through the amalgamation and meticulous preprocessing of diverse public datasets, encompassing variables such as maximum temperature, solar exposure, and precipitation levels, the study aims to unravel the intricate dynamics through which weather influences power resilience. We utilize over ten years of data from 47 local government areas. The analysis focuses on predicting future power outages using a state-of-the-art deep learning Long Short-Term Memory (LSTM) model. The results show a promising area under the Receiver Operating Characteristic (AUC ROC) curve of approximately 90% and a mean precision exceeding 96%. The experiments utilize a 5-fold cross-validation methodology to ensure robustness and reliability in the predictive model. It reveals the nexus between weather patterns and power systems and offers practical insights. The proposed work can serve as a valuable resource for all stakeholders in the energy sector, fostering informed decision-making and contributing to the ongoing dialogue on enhancing power resilience, improving cyber-physical infrastructure, and disaster preparedness.

INDEX TERMS Weather-induced power outages, power grid resilience, power outage prediction, deep learning, long short-term memory.

I. INTRODUCTION

In the vast landscape of smart grids, the quest for energy resilience has never been more pressing. The early knowledge of level of energy resilience with effects of climate change and sustainable energy are deemed important. Approximately 80% of power outages are due to weather related events [1] in United States of America alone. Panteli and Mancarella [2] reviews methodologies for modeling weather impact on power components, highlighting challenges. Emphasizing resilience as crucial for critical infrastructure, it outlines defense plans against extreme weather. Their research framework aims to model and prevent future weather-induced power disruptions, contributing to enhanced grid resilience. Panteli et al. [3] introduce a unified approach for evaluating and enhancing power grid resilience against extreme weather events. It incorporates a procedure for assessing severe weather impact, using fragility curves. The risk-based defensive islanding algorithm prevents cascading effects during emergencies, surpassing traditional infrastructure-based measures. Panteli et al. [4] addresses the rare but impactful events of extreme weather on power system resilience. It introduces a fragility model for individual components and the entire transmission system, focusing on wind events. A probabilistic multitemporal and multiregional resilience assessment methodology is proposed, utilizing

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optimal power flow and sequential Monte Carlo simulation. Risk-based resilience enhancement measures, driven by component resilience achievement worth, are evaluated using a test version of Great Britain's system. Panteli et al. [5] study the growing concern for resilience to high-impact, low-probability events, focusing on extreme weather impacts on global critical infrastructures. Introducing the resilience trapezoid, they extend the traditional triangle to quantify power system resilience, considering phases, time-dependent metrics, and enhancement strategies in real-time scenarios. Guikema and Nateghi [6] study the significant impact of natural disasters on society, causing widespread power loss. In the United States, severe weather and climate events lead to major outages, resulting in socioeconomic losses. Predictive models help utilities plan and respond efficiently, with Bayesian methods offering potential improvements by integrating structural reliability models with observed failure data. Agüera-Pérez et al. [7] study the pivotal role of meteorological conditions in microgrid energy management. Emphasizing the need for weather forecasts, the paper analyzes data sources, methodologies, and uncertainties in microgrid studies. Katal et al. [8] integrates CityFFD, a microclimate model, with CityBEM, an urban building energy model. The platform efficiently models urban areas, simulating a Montreal snowstorm to assess building resilience, providing high-resolution results. Microgrids offer a potential solution for power disruption events due to their islanding capability and support for renewable integration. Hussain et al. [9] conduct a three-step analysis to elucidate microgrids' role in enhancing power system resilience. It covers general resilience backgrounds, microgrids as resilience resources, and strategies employed by microgrids during major outages. Das et al. [10] explores climate-induced extreme events. It models the nexus of thermal resilience and energy efficiency in buildings. The study emphasizes evaluating energy efficiency for resilience enhancement, not just energy savings. Stone et al. [11] examines the increasing threat of critical infrastructure failures during extreme weather events in the United States. Investigating major grid blackouts and their alignment with heat waves, it employs a climate model and advanced building energy simulation. Their findings reveal recent events expose 68-100% of urban populations to heightened risks of heat-related illnesses. Weather-induced power shutdowns due to climate change drive research on community resilience. Hossain et. al [12] consolidates contributions on energy resilience and reliability, stressing the need for clear definitions in grid systems. Hamidieh and Ghassemi [13] study the escalating occurrence of global large-scale disturbances and the imperative to bolster power system resilience. Microgrids, integral to smart grids, emerge as pivotal tools for enhancing distribution system resilience against extreme events. Zhou [14] explores the pivotal role of energy resilience in ensuring the survival of district power systems during extreme events. Addressing inconsistencies in concept definition and quantification, it reviews the boundary and correlation with reliability, robustness, and flexibility in multi-energy systems.The study outlines multi-scale applications and future prospects for energy resilience, emphasizing its significance in district energy planning, design, and operation. The matter of energy efficiency [15] has been a focal point of research interest for the past decade. The digital twin allows for the simulation [16] of a variety of disruptions such as extreme weather occurrences, cyber-attacks, equipment failures, and rapid fluctuations in energy demand. Nyangon [17] emphasizes vulnerability to weather-related interruptions, underlining the significance of strategic collaboration for effective data governance. The combination of distributed energy resources, improved energy storage, demand-side management, and artificial intelligence is deemed critical. In this research, we:

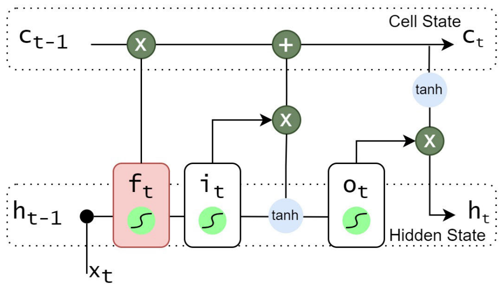

FIGURE 1. Inside an LSTM unit.

- Combine multiple public datasets, meticulously preprocess, filter, and integrate them to unveil the intricate nexus between meteorological conditions and power disruption events.
- Develop a cutting-edge deep learning Long Short-Term Memory (LSTM) model tailored for predicting future power outages by leveraging historical data from preceding days. This innovative approach showcases a novel method for forecasting within the energy sector.
- Conduct an in-depth analysis to scrutinize the impact of weather changes on power resilience in major Australian urban centers, aiming to derive pivotal insights that can enhance disaster preparedness and inform strategic infrastructure planning initiatives.

This study contributes significant insights by investigating the influence of weather conditions on power resilience. The proposed model shall have an impactful help for utility companies, legislators, and urban planners. They offer practical insights into what kind of improvements are needed to prevent such predictable weather-induced power outages throughout Australia and the rest of the world.

II. PRELIMINARY DISCUSSION

A. DEEP LEARNING AND LONG SHORT-TERM MEMORY

Deep Neural Networks (DNNs) and Long Short-Term Memory (LSTM) networks play critical roles in artificial intelligence. DNNs, with their numerous layers and linked nodes, specialize at managing the complex nature of raw data. They serve as strong building blocks in the vast field of artificial intelligence. [18]. DNNs are capable of hierarchical

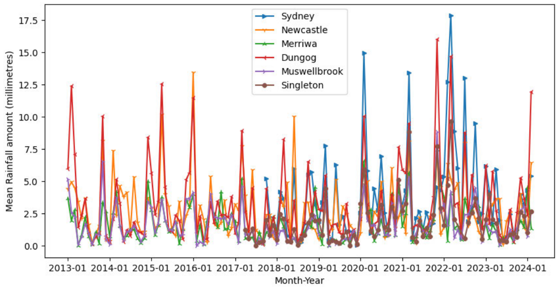

FIGURE 2. Mean (monthly) of recorded rainfall amount at different major weather stations.

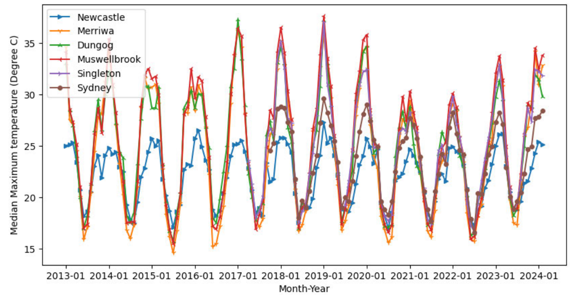

FIGURE 3. Median (monthly) of recorded maximum temperatures at different major weather stations.

feature extraction but struggle with temporal dependencies and prolonged sequential information. Enter the stage, LSTM networks - a specialized breed of recurrent neural networks (RNNs) engineered to navigate the intricate nuances of sequential data [19]. LSTMs exhibit a notable proficiency in capturing and retaining information across extended duration. Their strength particularly lies in applications involving time-series data, language modeling, and speech recognition within the domain of computer science research. The amalgamation of DNNs and LSTMs is no mere experiment; it is a strategic alliance that has proven instrumental in elevating the performance benchmarks across diverse applications. Combining the skill of deep neural networks in learning representations with the time-handling ability of LSTM networks has proven successful in various applications, as highlighted in studies like [20], [21], and [22]. The LSTM recurrent neural network unit comprises three gates and a cell state, depicted in Figure 1. These gates, namely the input gate i_t, forget gate f_t, and output gate o_t, play crucial roles in managing the cell state. The previous hidden state h_{t-1} is instrumental in generating a new hidden state and facilitating information processing through all gates.

The input gate i_t determines the amount of new input information to retain in the cell state:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{1}$$

Here, σ represents the sigmoid activation function, W_i and b_i denote the weight matrix and bias vector for the input gate, and $[h_{t-1}, x_t]$ signifies the concatenation of the previous hidden state and current input. The forget gate f_t regulates the information to be discarded from the cell state:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$

In this equation, W_f and b_f stand for the weight matrix and bias vector for the forget gate. The cell state gets updated based on the input gate, forget gate, and a candidate update:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{3}$$

Here, tanh denotes the hyperbolic tangent activation function, while W_c and b_c represent the weight matrix and bias vector for the candidate update. Finally, the output gate o_t determines how much of the cell state should be passed to the next hidden state:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{4}$$

The hidden state is subsequently updated as:

$$h_t = o_t \cdot \tanh(c_t) \tag{5}$$

III. ENVIRONMENT-INDUCED OUTAGES

A. GRID BLACKOUTS

There are multiple electric power distribution companies in Australia, among which Ausgrid is one such company. These companies provide live and past data regarding power outages. The data is available online [23] for customers' help and public record. We collect the publicly available data for Ausgrid power outages for 44 different quarters ranging from Q4, 2012, to Q4, 2023. This data is composed of 7 columns (Event ID, LGA, Start Date, Start Time, Customers Interrupted, Ave Dur. (min), Reason). Where LGA refers to the local government area, Start Date and Start Time indicate the date and time of the incident power outage. Reason provides a label for each unplanned power outage incident categorized with different reasons [24]. The data is compiled into one file for further analysis and discussion. LGA, being a limited area in terms of geographical scope, experiences weather conditions similar to that of the major city to which it belongs or is closely situated. There are 47 different LGAs listed with the outages information in the collected data, the nearest major weather stations are identified including Sydney, Newcastle, Singleton, Muswellbrook, Merriwa, and Dungog. The LGA are mapped with the nearest weather station, however, one of the LGAs labeled as Mid West Region is not considered for this study. The past data provided at different times have different date formats and there is some missing data for certain regions at certain times. Hence, only data from 2013 to 2023 outages are considered for this empirical study.

B. WEATHER DATA

The Australian Bureau of Meteorology provides access to different weather-related data measurements for numerous places in Australia. Among those, we select three commonly measured meteorological data, including the amount of rainfall in millimeters, temperatures in degrees Celsius, and

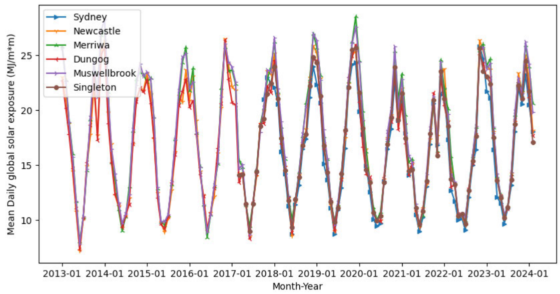

FIGURE 4. Mean (monthly) of recorded solar exposure at different major weather stations.

solar exposure in megajoules per square meter. All of these data variables are sampled at a daily frequency. The sampled data can be seen in figures 2, 3, and 4. The present study employs a rigorous technique to capture the central tendency of each variable, which informs the use of statistical measures like mean for rain and median for solar exposure and temperatures. Since the mean provides a meaningful measure of the average precipitation level and is sensitive to extreme values. Using it as the point estimate for rainfall is supported. However, because the median is robust to outliers and provides a more accurate depiction of the center value even in the presence of skewed distributions or anomalous data points, its usage for temperature and sun exposure is suitable.

C. WHERE THE ENDS MEET

Once the data of outages and weather is prepared as discussed earlier, it is ready to be further analyzed. The outages data is mapped to the weather data to see the correlation between the power failures and the weather conditions. As depicted in figure 7, the difference of amount rain recorded when the gird is working in normal manner vs when some outages are reported. It is seen that besides Dungog, all of the power station faced some outages when the rain was recorded. For all such locations, the average rain recorded is higher for the times when the outages occurred as compared to the normal operation. Sydney has the highest rain amount recorded at any day for the days with the power failure. However, the variance between Merriwa for days with normal and power failure days is much higher than the rest of the locations. The 5th and 95th percentile for the mean of the rain amount for all locations is recorded as 0.91 mil to 4.65 mil, respectively. Whereas as seen in figure 2, the monthly mean all time high of rainfall is recorded 17.5 mil. The daily median value for maximum temperatures seen in figure 5, show the central 90% interval of temperature ranging between 22.76 degrees Centigrade and 34.71 degrees Centigrade. Besides Sydney, for all locations the median temperatures is higher for the days when some power outages were recorded compared to normal operation. The difference of median temperature for power outages and normal operation is recorded highest for Dungog. However, the temperature difference for Newcastle remains negligible. The monthly median temperatures as seen in figure 3, show that the

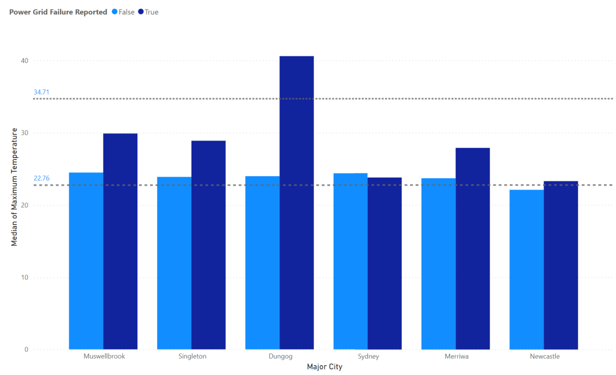

FIGURE 5. Median (daily) of recorded maximum temperatures at different major weather stations when the power outages happened vs normal operation.

highest monthly median is more than 35 degree Centigrade. While the lowest, remains below 20 degree Centigrade. The daily mean solar exposure recorded at all locations seen in figure 6 shows that the Sydney records higher exposure for the days no power outages compared to normal operation. For rest of the locations the said relationship is direct. The central 90% interval for mean daily solar exposure ranges between 15.3 (MJ/m^2) and 17.51 (MJ/m^2).

IV. DEEP LEARNING FORECASTING

We propose a deep learning model with a long short-term memory (LSTM) layer for forecasting possibility of power outage, based on the past weather measurements. The proposed model architecture is seen in figure 8. The data available from previous section is yet not mature enough to be used for proposed LSTM model. Feature engineering is applied to prepare this data for deep model training and evaluation. Initially a set 42 features are calculated Temperature, Solar Exposure, Rainfall Amount, Weather Station, three weather measurements of the previous day. For last three, four, and five days we calculate different point estimates for these weather measurements including mean, median, standard deviation, and variance. Furthermore, the samples undergo a rigorous filtering process, particularly concerning weather-related incidents, to guarantee that only outages caused by environmental factors are chosen. According to the electric distribution company's classification [24], four separate root causes make up the category of *equipment fault*. Notably, cases falling into this category are occasionally linked to extreme weather events, like heat waves or cold spells, where the local weather plays a role. An additional category of *environmental* includes a variety of elements, such as, but not restricted to, adverse weather and bushfire. Only incidents that can be directly linked to a lightning strike are included in the *lightning* category. We selected these three criteria to thoroughly study and understand how changing weather patterns affect the resilience of the electrical grid. Once these features are extracted, the contribution of these features is yet unknown, hence feature selection [25] is applied, using k highest score. For different k, the proposed

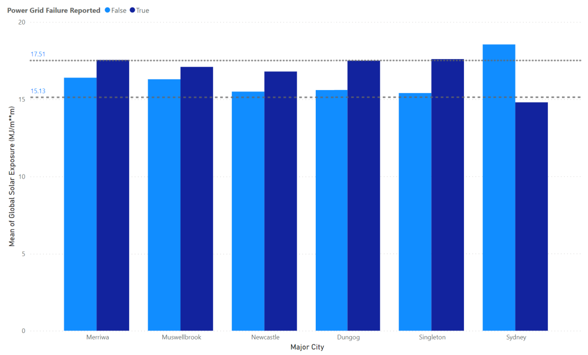

FIGURE 6. Mean (daily) of recorded solar exposure at different major weather stations when the power outages happened vs normal operation.

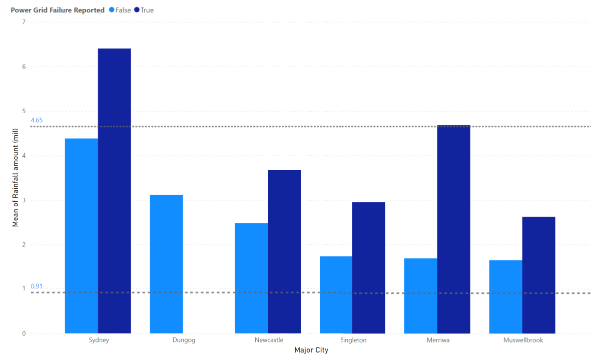

FIGURE 7. Mean (daily) of recorded rainfall amount at different major weather stations when the power outages happened vs normal operation.

model is trained and validated, [26] to identify more robust features. The training parameters used are set same for all features to benchmark the training and validation. A 5-fold cross validation approach is used, to ensure better coverage of the model. We used Adam optimizer with α as 0.001. Early stopping is used to save the best weights for each training. Multiple evaluation metrics [27] are considered in this study such that the a presence of a slight class imbalance, does not affect the reflection of the true evaluation of the proposed model. The accuracy to show overall performance relating to accurate predictions is defined as follows.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Count of all Predictions}} \tag{6}$$

To have further insight about the positive class's prediction the precision is defined as follows.

$$\text{Precision} = \frac{\text{TP}}{\text{Count of all Positive Predictions}} \tag{7}$$

Recall provides us the ratio for positive classifications classified as positive, is defined as follows.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{8}$$

The harmonic mean of aforestated two measures precision and recall is referred to as F1-score and define as follows.

$$\text{F1-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

In addition, a comprehensive statistical metric that reflects a thorough evaluation of a model's performance over a range of classification criteria is the area under the receiver operating characteristic curve (AUC ROC). The model's capacity to distinguish between positive and negative instances, so reflecting the trade-off between genuine positive rates and false positive rates, is shown by a larger AUC ROC.

Table 1 shows the resulting mean evaluations based on 5-fold cross validation.

The cross-validation analysis of the proposed model unveils compelling patterns across various feature set sizes, contributing to the depth of quality research in classification models. The minimum mean accuracy achieved is measured at 0.9 with three features, whereas for ten features it is observed as 0.91. This small progression highlights two sides of a coin, one that three features are sufficient enough to make a promising prediction. Also, a slight improvement is possible with ten features, however, the improvement being smaller shows that there is less room for improvement given the nature of the data. Similarly, the precision metric shows similar changes, with different number of features and highest mean precision is achieved with three features. The recall is observed as showing improvement with the increasing number of features.

TABLE 1. Cross-validation evaluation of proposed model for different feature sets.

Metric (mean 5-fold)	Feature Set Size			
	Three	Five	Seven	Ten
Accuracy	0.902	0.900	0.901	0.910
Precision	0.973	0.966	0.963	0.964
Recall	0.792	0.793	0.799	0.802
F1-Score	0.874	0.871	0.873	0.875
AUC ROC	0.888	0.886	0.888	0.900

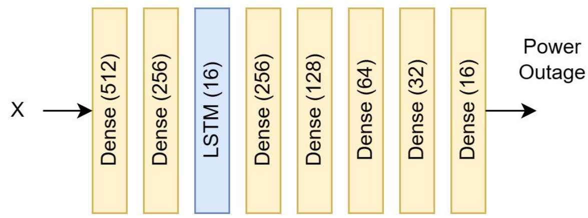

FIGURE 8. The proposed LSTM deep neural network architecture.

This robust performance, independent of feature set size, adds an element of reliability to the research findings. In the pre-processing stage, no samples are left out from the training and validation process, and naturally the data has imbalanced classes. Here, the F1-Score shows us a better perspective by balance of precision and recall. It is observed that for all the tested sizes of the features set the F1-Score remains stable at 0.87. A trend emerges in the AUC ROC metric, signaling that the model's discriminative capacity improves with larger feature sets. The values ascend from 0.888 with three features to 0.900 with ten features, illustrating the model's adeptness in navigating intricate data environments. This upward trajectory not only deliberates the model's discriminative strength but also enriches the research narrative by highlighting its capability to produce more accurate classifications as the feature set expands.

V. CONCLUSION

This research investigates the significant impact of weather-induced power outages. Employing an enriched methodology that involves data integration, cleansing, and preprocessing data from differently-natured public datasets. In this study we explore the direct impact of weather conditions on power resilience. We utilized over ten years of data from 47 local government areas in Australia. We proposed a cutting-edge deep learning Long Short-Term Memory (LSTM) model focusing on the prediction of power outages through recent past weather data. The findings reveal promising results based on standardized metrics we found the AUCROC curve at about 90% and a mean precision exceeding 96%. Highlighting the model's effectiveness in forecasting unplanned power blackouts. As noted in a detailed evaluation of the proposed model across varying feature set sizes. Consistent performance in accuracy and F1-score across different feature set sizes displays its strengths of identifying days where outages can be expected, with greater quality. The application of deep learning to explore other facets related to the behavior of the power grid and its resilience in diverse weather circumstances and other influencing factors is demonstrated.

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