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RESEARCH ARTICLE

Hybrid Artificial Intelligence Techniques for Enhanced Electricity Outage Prediction and Management in Distribution Networks

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ABSTRACT

This paper investigates outage management in electricity distribution networks through the application of artificial intelligence techniques. The core of the system utilizes a diverse dataset compiled from outage management system records, weather forecasts, and geographical data to predict potential electricity outages. The data is rigorously analyzed to determine correlations between various weather conditions and outage occurrences, with particular emphasis on the impact of wind speed and storm conditions. The predictive model, a cornerstone of this research, employs a hybrid artificial intelligence algorithm that integrates outputs from convolutional neural networks, recursive neural networks, and extreme gradient boosting. The predictions are further refined using a feedforward neural network and distributed to specific districts based on historical data trends. Comparative analysis against a naive model based on historical averages highlights the superior performance of the hybrid model, showcasing its reduced error rates and enhanced predictive accuracy. This decision support system not only provides reliable outage predictions but also facilitates more effective management strategies, thus improving operational efficiencies and customer service in electricity distribution. The findings underscore the potential of advanced analytics in transforming utility management and pave the way for further innovations in smart grid technology and outage prevention strategies.

Index Terms—Artificial intelligence, decision support systems, electricity distribution, outage management

I. INTRODUCTION

The modern distribution system is a complex network that requires a high-speed, precise, and reliable protection system. Faults in the distribution system are inevitable, and overhead line failures are often more frequent compared to other main components. Faults not only affect the system's reliability but also significantly impact end-users. The protection of transmission and distribution lines is becoming increasingly complex, leading to more complicated protection configurations. Therefore, high-accuracy fault prediction enhances the operational balance and reliability of the distribution system and helps prevent major energy outages.

The primary question addressed by this research is: How can artificial intelligence (AI) techniques improve the prediction and management of electricity outages in distribution networks?

The hypothesis posited by this research is that a hybrid AI model integrating convolutional neural network (CNN), recursive neural networks (RNN), and extreme gradient boosting (XGBOOST) can significantly enhance the accuracy of outage predictions compared to traditional models. By leveraging comprehensive datasets encompassing OMS records, weather forecasts, and geographical information, the proposed AI-based system is expected to provide superior predictive performance, thereby facilitating more effective outage management and improving overall service reliability and operational efficiency in electricity distribution.

Electricity distribution companies (DisCom) use outage management system (OMS) to better manage and monitor their networks under supply continuity criteria. Through OMSs, DisComs manage processes such as the detection of outages, identification of fault locations, informing affected customers, workforce management, re-energizing the system after fixing faults, keeping fault records, and conducting necessary reporting.

Outage management system records allows for real-time monitoring of the network and direct information from actions on the network. In the event of a fault, immediate management and direction of the

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workforce can be conducted. However, all these processes need to be urgently planned according to the occurring fault, thus presenting an unplanned, difficult-to-manage, and error-prone workload. Additionally, the failure to track the fundamental causes of faults occurring in all distribution elements within the DisComs' coverage areas leads to prolonged fault durations and disrupts system operational continuity. Fault predictions, while the responsibility of the operational personnel, are not systematically approached and are typically based on the personnel's experiences. Aside from periodic maintenance, repair and maintenance planning are conducted after a fault has occurred, leading to time loss and inefficient work.

The developed system will improve service quality parameters of DisComs, efficient operation, economic personnel management, and quick and economical decision-making. Meeting the expectations of the quality factor (QF) application and QF improvements made by the Energy Market Regulatory Authority is intended.

Machine learning methods are used to predict the percentage of potential fault situations that DisCom's low voltage and high voltage network elements might encounter weekly based on the cumulative total of faults they have previously experienced. Thus, operational staff can be informed about possible faults in the equipment they are responsible for 1 week in advance, and the developed algorithm will provide reports of maintenance plans for predicted faults, showing which maintenance plan, if implemented, could prevent the fault from occurring. From this perspective, the percentage-based fault prediction scenarios will be developed for any element under the responsibility of the DisCom for the following week, thus identifying potential fault points and determining the maintenance plan for the predicted fault. The algorithm meets the necessary work benchmarks to reduce the previously specified fault duration.

Reducing fault durations is a critical factor in improving supply continuity. The creation of estimated fault scenarios, organization of specific maintenance plans, rapid identification of fault points, and the ability for field personnel to quickly apply the correct methods are important work benchmarks in better managing the process.

Main Points

- The use of artificial intelligence (AI) in managing electricity outages, utilizing a hybrid AI algorithm that combines convolutional neural networks, recursive neural networks, and extreme gradient boosting, enhanced by feedforward neural network for precise predictions based on weather and geographical data, is explored.
- The predictive system outperforms traditional models by analyzing relations between weather conditions and outages, particularly focusing on winds and storms, to forecast potential disruptions more accurately.
- The enhanced decision support system not only optimizes outage management but also advances smart grid technologies and preventive strategies, significantly improving service reliability and operational efficiency in electricity distribution.

At this point, the main goal of the paper is to develop a systematic approach using AI technology alongside the likelihood of failures in network equipment such as transformers, overhead lines, and breakers. This involves processing data from the OMS database, which contains a wealth of information about equipment (which DM, which feeder, etc.), related previous faults, the equipment's voltage level, geographical climatic information, and the age of the equipment, to predict weekly potential faults for each network element, creating maintenance plans to preempt predicted faults and prioritizing proposed maintenance plans based on factors like calculated unserved energy, interruption duration, and the number of customers affected.

II. LITERATURE REVIEW

As global energy demand increases rapidly, electricity is among the fastest-growing energy sources. [1]. The increasing dependency on electricity worldwide causes interruptions or faults in electric services to create significant disruptions in daily life and lead to economic losses. Therefore, while trying to provide the most reliable service to their customers, DisComs strive to make the best use of past experiences of electricity outages. These companies attempt to take preventive measures to repair faults and reduce the duration of outages after they occur. Both the increased analytical capabilities of algorithms and the improved accuracy of short-term weather forecasts provide opportunities for DisComs to predict the number and duration of electric outages and make decisions to minimize these interruptions.

According to the International Association for Energy Economics, a 1-hour power outage in Türkiye would cost the national industry 18 million TL in damages [2]. Reporting the duration of these outages can significantly reduce the damage. In this context, knowing where unplanned power outages will occur and how long they will last, in addition to planned maintenance outages, will increase trust in companies responsible for electricity distribution infrastructure.

In the literature on outage prediction, models have been developed that take weather forecasts as input, primarily because most of the causes are weather-related. An electric outage in a specific geographic area can be predicted for the number of customers affected, the duration customers are without electricity, the duration of a specific outage, or the number of outages occurring in a region over a certain period. Accurately predicting these characteristics helps forecast the costs associated with the outage and aids in planning repair or reconstruction operations and workforce management.

According to an annual report prepared by Eaton, using forecast data related to lightning strikes, precipitation, wind speeds, and temperatures has improved the prediction of an event's impact. The report reveals that a 5% annual increase in wind speed increases the number of customers affected by outages by 56% for that year, and a 10% annual increase in precipitation per square meter increases the number of customers affected by outages by 10% [3]. Research by Lawrence Berkeley National Laboratory and Stanford University indicates statistically significant correlations between the average annual number of outages a customer experiences and predictive variables such as wind speed, precipitation, lightning strikes, the number of customers per kilometer of line, daily cooling degrees, and the distribution of underground transmission and distribution lines. The study also suggests that the increasing severity of major events over time is a primary reason for the trend in the duration of power outages [4].

In the literature, methods have been developed to predict the duration and number of outages, but these methods tend to overlook instant outages and storms. One of the earliest studies in outage prediction by Brown and others proposes models aimed at determining the reliability of a power system [5]. The study emphasizes the need to consider weather-related events such as storms, which typically cause long-duration and continuous outages, in predictions. A study from the early 2000s by Balijepalli et al [6] used the widely used Monte Carlo Simulation to calculate the rate of faults caused by lightning in power systems. This study modeled the reliability of the system based on storm characteristics and the system's response to lightning conditions. Zhou et al [7] compare the Poisson regression model with the Bayesian network model. Yang et al [8] also used Poisson regression to roughly determine failure rates related to weather conditions. Their results show that the greatest impact on the reliability of power systems, similar to other studies, stems from wind, ice, and lightning events. However, all these studies focus on determining how weather-related events annually affect the reliability of the power system, not predicting expected hourly outages using specific weather events.

Reed [9] determined that the gamma distribution is a good indicator of outage duration and that the square of storm speed is the best predictor of outage duration in the energy system. However, the study also adds that wind speeds should not be the only parameter used to predict electric outages, and including precipitation and other weather forecast parameters makes predicting outage duration more complex. Liu et al [10] developed Poisson and Negative Binomial Generalized Linear Models to explain the trends in electricity outages and identified the most significant variables explaining changes in electricity outages as maximum wind power, the number of transformers, and hurricanes.

In another study, Liu et al [11] argued that models could be better developed using explanatory variables related to trees (e.g., number, type, age of trees, and frequency of tree cutting) and infrastructure variables (age and condition of cables) to predict outage durations related to weather conditions.

Some studies in the literature on electricity outage predictions have used decision tree structures. Guikema et al [12] used both regression-based models and data mining approaches (Classification and Regression Trees (CART) and Bayesian Regression Trees (BART)) to predict power system outages and outage durations. Their studies indicated that data mining approaches performed better than regression-based approaches. [13] developed a two-stage model using CART and Poisson regression model to predict the number of electricity outages. The CART algorithm was used to model whether a location would experience an electricity outage, while the Poisson regression model was used to predict the number of electricity outages at a specific location. Their studies do not include predictions of the number of customers affected by an outage or the duration of a specific outage at a location.

Guikema et al [14] developed a spatially generalized electricity outage prediction model (SGHOPM) for the entire Gulf Coast and East Coast of America. This study showed that spatially generalized models are useful to utility companies and emergency managers as both operational and risk management tools. McRoberts et al [15] improved the SGHOPM algorithm developed by Guikema and others by adding local environmental variables. He et al [16] conducted another study using two statistical methods. In their study, they input variables such as soil moisture, land cover, power infrastructure locations, and categorical tree leaf phenology with weather forecast values into BART and Quantile Regression Forests models. They suggested that the performance of the model changes depending on the spatial resolution and recommended applying both models together to predict outages at multiple spatial resolutions [16].

In addition to purely using decision trees, studies have also been conducted to develop electricity prediction models using boosted (ensemble) decision trees. Kankanala et al [17] found that the AdaBoost enhanced NN algorithm performed better than other modeling methods, including traditional neural networks and linear regression models.

Besides decision trees and regression models, models based on artificial neural networks (ANNs) have begun to be frequently used in electric outage prediction. [18] used an ANN and support vector machine approach to detect faults in radial distribution systems. Unlike traditional fault prediction methods, they used measurements found in transformer stations, circuit breakers, and relay conditions. The results indicated the feasibility of applying the proposed method in practical distribution system fault diagnostics.

Jamil et al [19] attempted to predict fault locations on transmission lines in their study. They used feedforward neural networks (FFNNs) and tested them in different operating conditions, improving success rates compared to traditional fault location prediction methods. Combining the neural network with multi-resolution analysis based on wavelet transformation was effective in reducing fault location prediction errors.

Because the electricity outage problem involves predicting both the duration and location of outages, it is a type of spatiotemporal problem. In many real-world applications such as intelligent transportation, urban planning, public safety, health, and environmental management, extracting valuable information from spatiotemporal data is critically important. As the number, volume, and resolution of spatiotemporal datasets rapidly increase, traditional data mining methods are insufficient. In recent years, the development of deep learning techniques and their strong hierarchical feature learning capabilities, both spatially and temporally, have led to the use of deep learning in this field. Deep learning methods, such as CNN and RNN, are often used to solve spatiotemporal problems [20-22].

Due to the spatiotemporal characteristics of the electricity outage problem and the increase in computing power of machines, a shift towards deep learning techniques in solving the problem is expected.

III. DEVELOPMENT OF THE DECISION SUPPORT SYSTEM

In this paper, AI algorithms are used to process historical fault data from Aydin–Denizli–Muğla distribution area, along with OMS records and meteorological and geographical information from the fault locations. This data serves as training data for a predictive model, which forecasts the types of faults that could occur in different network elements 1 week into the future. The model continuously learns and increases in accuracy over time as it processes accumulating fault data, meteorological forecasts, and geographical information.

The developed system serves as a decision-making tool for users in case of potential faults. One of the objectives of setting up the system as a DSS is to provide deeper insights for planning fault interventions and, when necessary, prioritize faults. Accordingly, an algorithm is designed that can create maintenance plans for predicted faults and prioritize these maintenance plans based on criteria such as the number of customers affected and energy not supplied.

A. Assumptions

Weather forecasts are one of the primary inputs in the algorithms. The weather data used in this paper consists of both historical and forecast data. According to the official page of the General Directorate of Meteorology under the Ministry of Agriculture and Forestry:

- Monthly forecasts are prepared based on the data and products of the European Centre for Medium-Range Weather Forecasts, of which Türkiye is a founding member and supported by 34 countries, mostly members of the European Union.
- The monthly forecast model is designed to predict large-scale weather events (air masses, fronts, mid-latitude pressure systems). Smaller-scale local meteorological events may not be represented.
- Weather temperature and precipitation averages are considered and evaluated as being below or above seasonal normals and updated twice a week.
- Due to its geographic location, the model's accuracy is generally higher in summer and winter months compared to spring. Temperature is generally a more reliably predicted parameter than precipitation.
- Since different methods and tools are used in short, medium, and long-term forecasts, there may be differences with other published forecast products.

For city and district centers regarding weather forecasts:

- Hourly forecasts in the expected event formulation represent the weather conditions of the past 3-hour period.
- The wind gust parameter in hourly forecasts represents the sudden increase in wind speed during the past 3 hours.
- Felt temperature parameter in hourly forecasts is calculated based on the predicted air temperature at the same hour along with relative humidity and wind values. This temperature is a subjective concept as it is influenced by climatic environment, clothing thermal resistance, body structure, and personal condition as much as by meteorological factors such as thermometer temperature, relative humidity, wind, and radiation.

B. System Architecture

Users can access fault predictions through OMS web and mobile applications and make configuration changes to the system. Weather data is transferred to the OMS system via Rest-API service. Similarly, load data for distribution transformers is transferred from the Automatic Meter Reading System (OSOS) system to the OMS system via Rest-API service. AI algorithms that generate forecasts receive OSOS and weather data through Rest-API services from OMS. They write their forecasts directly into the OMS database. Forecasts recorded in the OMS database are presented to users on mobile and web platforms.

C. Definition of AI Models in the System Definition

The recording hierarchy, device, channel, tag definitions, and updates of prediction data in the OMS system have been explained.

Prediction model results are added to the OMS system as a data source. In the OMS, data sources are defined as devices. A standardized identification method allows different prediction models to be implemented or removed. If desired, data flow from the prediction model can be stopped.

1) Data Recording Hierarchy in The OMS

- Device: The prediction model is added as a device. Device refers to a system element that can measure and record. As the service providing meteorological data is also a data source, it is defined as a device in the system.
- Channel: Units where predictions are made are defined as channels connected to the device. Units can be added as departments (district) or distribution centers. The channel structure allows the prediction model to be applied on a unit basis instead of the entire distribution area, making the system dynamic. It enables the application of the prediction model for desired departments. For instance, if the prediction model works well in the Bodrum district but not in Marmaris, the channel for Marmaris can be deactivated in the system. This provides a significant advantage in maintaining the model's performance, especially in regional mismatches in input data sources affecting the model's outcome (e.g., regional inconsistencies in weather data).
- Tag: Tags are added for parameters resulting from the prediction model. Tags used as outputs of the prediction model are specified below:
    - Total number of faults
    - Number of faults with a duration of 0–1 hours
    - Number of faults with a duration of 1–3 hours
    - Number of faults with a duration of 3–6 hours
    - Number of faults lasting over 6 hours
    - Total fault duration
    - System Average Interruption Duration Index (SAIDI)
    - System Average Interruption Frequency Index (SAIFI)
    - Total number of affected subscribers

For example, the configuration structure for a prediction model is as follows:

- Device: Fault Prediction Model 1
    - Channel 1: Bodrum
        - Tag 1: Total number of faults

    - Tag 2: Number of faults with a duration of 0–1 hours
    - Tag 3: Number of faults with a duration of 1–3 hours
    - Tag 4: Number of faults with a duration of 3–6 hours
    - Tag 5: Number of faults lasting over 6 hours
    - Tag 6: Total fault duration
    - Tag 7: SAIDI
    - Tag 8: SAIFI
    - Tag 9: Total number of affected subscribers
  - Channel 2: Marmaris
    - Tag 1: Total number of faults
    - Tag 2: Number of faults with a duration of 0–1 hours
    - Tag 3: Number of faults with a duration of 1–3 hours
    - Tag 4: Number of faults with a duration of 3–6 hours
    - Tag 5: Number of faults lasting over 6 hours
    - Tag 6: Total fault duration
    - Tag 7: SAIDI
    - Tag 8: SAIFI
    - Tag 9: Total number of affected subscribers

Predictions from the models are produced for 72 hours ahead in hourly intervals. Predictions are created daily, and multiple prediction values for the same date and time are recorded. These values serve as a data source to show prediction trends. Particularly with weather forecasts becoming clearer the day before, changes in fault predictions may occur.

2) Recording Weather Data Definition

The recording hierarchy, device, channel, tag definitions, and updates of meteorological data in the OMS system have been explained. Information about the recording method and usage of alerts and warnings from the Meteorological Data Service in OMS has been provided.

Meteorological data is transferred to the OMS system via a web service and recorded in the database for use in software. Each prediction point (district center) is recorded in megawatt/hour (MWM), and meteorological parameters are defined separately for each point.

The recording hierarchy of measurement points in the OMS system is specified below:

- Device: The Meteorological Data Service is added as a device. Device refers to a system element that can measure and record. Since the service providing meteorological data is also a data source, it is defined as a device in the system.
- Channel: Each prediction point is added as a channel connected to the device. If data collection from the prediction points where meteorological data is received is to be stopped or a new prediction point is to be defined, management can be done from the device management area in the application.
- Tag: Each meteorological parameter is defined as a tag in the system. Management of parameters and alarm definitions is done through tags. The meteorological parameters used for prediction are listed below:
  - Precipitation
  - Temperature
  - Wind power
  - Radiation
  - Cloud cover percentage
  - Humidity

For example, the configuration structure for a prediction point is as follows:

- Device: Meteorological Data Service
  - Channel 1: Bodrum
    - Tag 1: Precipitation
    - Tag 2: Temperature
    - Tag 3: Wind power
    - Tag 4: Radiation
    - Tag 5: Cloud cover percentage
    - Tag 6: Humidity
  - Channel 2: Marmaris
    - Tag 1: Precipitation
    - Tag 2: Temperature
    - Tag 3: Wind power
    - Tag 4: Radiation
    - Tag 5: Cloud cover percentage
    - Tag 6: Humidity

3) Recording OSOS Transformer Load Data Definition

The recording hierarchy, device, channel, tag definitions, and updates of transformer load data from the OSOS system in the OMS system have been explained. Transformer load data from the OSOS system is transferred to the OMS system via a web service. Data is recorded based on transformers, and the transformer and distribution center matching are retrieved from the Geographic Information System (GIS) system. Past load information for each transformer is used as input for the algorithm. The recording hierarchy of the data is explained below:

- Device: OSOS Data Service is added as a device. Device refers to a system element that can measure and record (RTU, IED, etc.). Since the OSOS data service is also a data source, it is defined as a device in the system.
- Channel: Each transformer is added as a channel connected to the device.
- Tag: Load data is added as a tag.

IV. DECISION SUPPORT SYSTEM APPLICATION

A. Data Sources

Data sources that can be evaluated for fault analysis in this paper are shown in Table I. In the electricity distribution network, weather conditions are one of the major factors of faults in overhead networks. During the test data preparation, priority was given to fault data and weather data.

1) OMS Data

Unplanned outage data from 2018 to 2023 are collected from OMS and included in the system. Data available from OMS for the dataset is presented in Table II.

2) Weather Data

Hourly forecast data for the same period are obtained from the Ubimet data source. Parameters of the weather data collected from Ubimet are shown in Table III.

TABLE I.
DATA SOURCES

N	Main Source	Description
1	OMS	Outage data
2	Weather data	Weather related data
3	GIS	Network data
4	WFM	Fault location data, Used materials
5	Geographic information	Regional geographic data
6	EAM	Maintenance data
7	OSOS	Electrical power data
8	SCADA	Electrical power data, fault current information
9	MBS	Subscriber information (tariffs, consumption)

GIS, geographic information system; OMS, outage management system.

TABLE II.
OMS DATA PARAMETERS

ID
Level
Department
Distribution center
Switching point
Province
District
Neighborhood/village
Street
GIS ID
Outage reason
Cause
Source
Duration
Notification
Outage duration
Start time
End time
Urban area HV subscriber
Urban area LV subscriber
Rural area HV subscriber
Rural area LV subscriber
Affected load
Affected transformer count
Unsold energy
Priority
Main level

HV, high voltage; LV, low voltage.

B. Methodology

1) Categories

Predictions are classified according to the duration of the outages. Outages are classified into four categories based on duration:

- Category 1: Outages lasting less than 1 hour
- Category 2: Outages lasting longer than 1 hour and less than 3 hours
- Category 3: Outages lasting longer than 3 hours and less than hours
- Category 4: Outages lasting longer than 6 hours

2) Characteristics of the Outages

The developed algorithm predicts the total number of outages and the number of outages classified by duration for each hour within the next 72 hours in the provinces and their associated districts. The outage prediction algorithm uses AI methods to generate predictions. Thus, a sufficient number of outages must have occurred, and this pattern must be modeled by the algorithm.

Upon reviewing the outages in the districts, it is observed that many districts have not experienced a sufficient number of outages to yield accurate results from learning methods. Additionally, it is not possible to obtain weather data specific to each district, which is a fundamental input for the model. Therefore, the outage prediction algorithm makes total and four-category classified outage predictions for the three provinces in the Aydin–Denizli-Muğla region and then distributes these predictions to the associated districts. This distribution uses the ratio of outages that occurred in each district over a certain period to the outages that occurred in the relevant province.

The developed algorithm for hourly outage prediction uses past outages and their durations along with the general weather forecast for the province. The weather data includes humidity, cloud cover, radiation, wind speed, wind direction, temperature, and precipitation probability. The scope of the dataset is from August 2018 to March 2023, and the frequency is hourly.

3) Theoretical Background

Forecasting model output can be represented as (1):

$$P(t) = f(W_t, H_t, G_t) \tag{1}$$

Where

P(t): Represents the predicted number of outages at time *t*.

TABLE III.
WEATHER DATA

Temperature
Dew point
Cumulative precipitation
Snow line
M line
Relative humidity
Wind speed
Wind direction
Gust
Precipitation probability
Snow probability
Sunshine duration
Cloud cover
Max radiation
UV radiation
Symbol
Snow depth
Precipitation
Direct radiation
Diffuse radiation
Surface radiation

f(): Denotes the forecasting function, which is modeled using AI techniques (e.g., CNN, RNN, XGBOOST).

W_t: Weather data at time *t*, including parameters like wind speed, precipitation, and temperature.

H_t: Historical outage data up to time *t*.

G_t: Geographical data relevant to the distribution network.

Detailed Steps:

1. Input weather data (W_t): Collect data on various weather parameters known to affect outages.
2. Incorporate historical data (*H*): Use past outage records to identify patterns and trends.
3. Utilize geographical information (G_t): Include data such as terrain type, urban/rural classification, and proximity to key infrastructure.

The forecasting function *f* processes these inputs to predict the number of outages *P(t)*.

The error at time t can be calculated using the (2):

$$E(t)=\frac{1}{N}\sum_{i=1}^{N}\left|P_i(t)-O_i(t)\right| \tag{2}$$

Where

$E(t)$: Represents the error at time *t*.

N: Total number of prediction instances.

$P_i(t)$: Predicted outages for instance *i* at time *t*.

$O_i(t)$: Observed outages for instance *i* at time *t*.

Detailed Steps:

1. Calculate absolute error: For each instance *i*, compute the absolute difference between predicted $P_i(t)$ and observed $O_i(t)$ outages.
2. Average the errors: Sum the absolute errors for all instances and divide by the total number *N* to get the average error $E(t)$.

This equation helps in assessing the accuracy of the forecasting model by measuring the average deviation of predictions from actual values.

The distribution of predicted outages to specific districts can be represented as (3):

$$D(d,t)=\frac{\mathrm{P}(\mathrm{t})\times\mathrm{R}(\mathrm{d},\mathrm{t})}{\sum_{d=1}^{D}R(d,t)} \tag{3}$$

Where

$D(d,t)$: Distributed predicted outages for district d at time *t*.

$P(t)$: Total predicted outages at time *t* (from1).

$R(d,t)$*:* Ratio or historical weight of outages in district *d* at time *t*.

$\sum_{d=1}^{D}R(d,t)$: Sum of ratios for all districts, ensuring normalization.

Detailed Steps:

1. Compute historical ratios: Determine the historical proportion of outages in each district $R(d,t)$.
2. Calculate total outages: Use the total predicted outages $P(t)$ from (1).
3. Distribute outages: Multiply $P(t)$ by the ratio $R(d,t)$ and normalize by the sum of all ratios to get the distributed prediction $D(d,t)$.

This equation allocates the total predicted outages to individual districts based on historical data, ensuring that predictions are contextually accurate for each district.

4) AI Models

Model 1. CNN

The CNN algorithm has been successful in image processing problems in recent years. The convolution process, which occurs through filters on the pixels that make up the image, identifies patterns in the image, and the repeated process of this operation generates results. In Model 1, weather data and past outage values are used as inputs in the developed CNN algorithm, and predictions for the next 72 hours are generated as outputs.

Model 2. XGBOOST

XGBOOST is a decision tree-based model. The model resamples the input space repeatedly to create new datasets and produces results using regression trees (weak learners) generated from these sets. The input for this model, as in Model 1, includes weather data and past outage data.

Model 3. RNN

The RNN algorithm is a deep learning method used to model time-dependent data. The RNN algorithm uses past outage values to calculate the hidden states of these outages, performs pattern recognition, and predicts the future by integrating these states with past outage data. It is evident that the outages, as a result of external factors, create a pattern over time. Therefore, outages can be predicted using past outage data. This model uses past 120-hour outage data as input and generates predictions for the next 72 hours.

Model 4. Hybrid Model as FNN

The provincial-level outage prediction hybrid learning algorithm is developed to make more accurate predictions using the forecasts from the above three models. In predictive modeling literature, such as energy price prediction and demand forecasting, hybrid models have shown superiority over individual models. The developed hybrid algorithm reduces the error amount made by individual models and produces better predictions as a result. This algorithm predicts outages for the next 72 hours at the provincial level through the FNN algorithm, which is a type of deep learning structure. The FNN algorithm processes the input set in hidden layers through nonlinear transformations to produce output.

5) Stages of the AI Algorithm

The developed algorithm works in three stages. First, it predicts outages at the provincial level for the next 72 hours hourly, then distributes these outage predictions to the district level. The model that predicts at the provincial level is a hybrid learning algorithm. The hybrid learning algorithm aims to achieve better results by using the outcomes produced by different learning models. The results fed to the hybrid algorithm come from CNN, RNN, and XGBOOST models. After obtaining results from these models, final prediction results are generated with a new FNN algorithm. Additionally, a model has been developed that predicts outages in four categories based on outage duration at the provincial level.

In the first stage, model 4 (Hybrid Model) predicts the total number of outages and outages classified into four categories by duration for the next 72 hours at the provincial level.

In the second stage, the total outage predictions produced are distributed to the districts associated with the province based on the ratio of outages that occurred in the last 3 months. For example, if the predicted number of outages at 12:00 PM on April 20, 2020 is 10 and 20% of the outages that occurred in Muğla province at 12:00 PM over the last 3 months occurred in Bodrum, then the predicted number of outages for Bodrum at 12:00 PM on April 20, 2020 is 2.

In the third stage, the predictions made in the districts are classified into four categories. This process is based on the ratio of outages that occurred in the last 3 months in four categories to the total outages that occurred in the last 3 months. For example, if the predicted number of outages for Bodrum at 12:00 PM on April 20, 2020 is 2 and the ratios of outages that occurred at 12:00 PM in Bodrum, classified by outage duration, are 35%, 40%, 25%, and 10% respectively, then the predictions for Bodrum at 12:00 PM for the four categories are (2, 2, 0, 0) respectively.

V. RESULTS AND DISCUSSION

A. Provincial Level Results

Prediction results of individual models and the most basic model in the literature, the naive model, are compared with the predictions produced by the developed hybrid model using the performance metrics mean absolute error (MAE) and mean squared error (MSE) (Tables IV–VI). The expectation from this comparison is that the hybrid model will perform better than the individual models and the naive model. The naive model predicts the next 24 hours of outages based on the previous 24 hours. This comparison with the naive model is a basic method to check whether the developed AI models can produce better results than the simplest benchmark model.

TABLE IV.
AYDIN PROVINCIAL TOTAL OUTAGE PREDICTION ERROR RESULTS

Aydın	MAE	MSE
Model 1	0.180	0.9216
Model 2	0.186	1.0568
Model 3	0.240	0.9801
Model 4	0.180	0.3481
Naive	0.310	1.9600

TABLE V.
DENIZLI PROVINCIAL TOTAL OUTAGE PREDICTION ERROR RESULTS

Denizli	MAE	MSE
Model 1	0.220	2.3747
Model 2	0.317	2.7225
Model 3	0.210	0.9216
Model 4	0.20	0.450
Naive	0.361	3.7249

TABLE VI.
MUĞLA PROVINCIAL TOTAL OUTAGE PREDICTION ERROR RESULTS

Muğla	MAE	MSE
Model 1	0.420	2.5600
Model 2	0.447	4.1047
Model 3	0.260	1.9600
Model 4	0.213	1.1278
Naive	0.321	3.2400

Results show that the error of the developed hybrid model is lower than the prediction errors produced by the individual models and the naive model. Thus, the developed model is superior to the individual models and the naive model.

B. District Level Results

Prediction results made by the developed algorithm for the districts in the Aydın–Denizli-Muğla distribution region are compared with the naive model. As can be seen from the Tables VII–IX, the errors produced by the AI models are lower than those of the naive model.

VI. CONCLUSION

The development and deployment of the DSS described in this paper mark a significant advancement in the management of electricity distribution networks. By integrating machine learning and deep learning techniques, particularly through a hybrid model combining CNN, RNN, and XGBOOST algorithms, the system effectively predicts electricity outages with greater accuracy than traditional models. The utilization of a comprehensive dataset, including outage data, weather conditions, and geographical information, allows for nuanced analysis and improved prediction capabilities.

TABLE VII.
OUTAGE PREDICTION ERROR RESULTS FOR DISTRICTS IN AYDIN

Aydın	Bozdoğan	Buharkent	Didim	Efeler	Germendik	Karacasu	Karpuzlu	Koçarlı	
MSE (Model 4)	0.190	0.044	0.450	0.463	0.154	0.056	0.046	0.120	
MSE(Naive)	0.215	0.066	0.464	0.447	0.194	0.129	0.121	0.166	
MAE (Model 4)	0.198	0.044	0.521	0.592	0.192	0.056	0.050	0.123	
MAE(Naive)	0.291	0.073	0.752	0.710	0.252	0.159	0.149	0.212	
Aydın	**Kuyucak**	**Kuşadası**	**Köşk**	**Nazilli**	**Sultanhisar**	**Söke**	**Yenipazar**	**Çine**	**İncirliova**
MSE(Model 4)	0.056	0.500	0.056	0.356	0.069	0.404	0.054	0.263	0.104
MSE(Naive)	0.114	0.484	0.110	0.369	0.116	0.403	0.088	0.322	0.168
MAE(Model 4)	0.065	0.538	0.065	0.385	0.077	0.467	0.058	0.442	0.125
MAE(Naive)	0.135	0.792	0.128	0.548	0.139	0.651	0.099	0.482	0.211

TABLE VIII.
OUTAGE PREDICTION ERROR RESULTS FOR DISTRICTS IN DENIZLI

Denizli	Acıpayam	Babadağ	Baklan	Bekilli	Beyağaç	Bozkurt	Buldan	Güney	Honaz	
MSE (Model 4)	0.333	0.019	0.013	0.044	0.006	0.031	0.106	0.054	0.117	
MSE(Naive)	0.446	0.019	0.013	0.044	0.006	0.035	0.135	0.067	0.133	
MAE (Model 4)	0.249	0.034	0.032	0.047	0.040	0.063	0.166	0.077	0.070	
MAE (Naive)	0.333	0.042	0.035	0.055	0.044	0.076	0.203	0.092	0.083	
Denizli	**Merkezefendi**	**Pamukkale**	**Sarayköy**	**Serinhisar**	**Tavas**	**Çal**	**Çameli**	**Çardak**	**Çivril**	**Kale**
MSE (Model 4)	0.423	0.344	0.013	0.044	0.167	0.071	0.110	0.013	0.402	0.067
MSE (Naive)	0.502	0.365	0.017	0.056	0.192	0.083	0.110	0.013	0.473	0.092
MAE (Model 4)	0.362	0.368	0.064	0.066	0.195	0.087	0.118	0.038	0.324	0.103
MAE (Naive)	0.618	0.565	0.075	0.075	0.262	0.109	0.147	0.041	0.478	0.129

TABLE IX.
OUTAGE PREDICTION ERROR RESULTS FOR DISTRICTS IN MUĞLA

Muğla	**Bodrum**	**Dalaman**	**Datça**	**Fethiye**	**Kavaklıdere**	**Köyceğiz**	
MSE (Model 4)	0.656	0.113	0.098	0.510	0.081	0.090	
MSE (Naive)	0.666	0.191	0.156	0.501	0.088	0.184	
MAE (Model 4)	1.269	0.125	0.115	0.673	0.106	0.098	
MAE (Naive)	1.259	0.256	0.190	0.884	0.105	0.224	
Muğla	**Marmaris**	**Menteşe**	**Milas**	**Ortaca**	**Seydikemer**	**Ula**	**Yatağan**
MSE (Model 4)	0.502	0.379	0.644	0.158	0.521	0.140	0.258
MSE (Naive)	0.366	0.405	0.665	0.241	0.417	0.173	0.247
MAE (Model 4)	0.744	0.429	1.094	0.204	1.488	0.169	0.371
MAE (Naive)	0.577	0.665	1.285	0.318	0.720	0.226	0.320

The implementation of the system demonstrates a clear enhancement in predictive accuracy, as evidenced by the reduced error rates when compared to a naive model based on historical averages. This accuracy is crucial for effective preemptive actions and optimizing resource allocation in outage management. Furthermore, the ability to classify predicted outages into four time-based categories allows for more specific and effective response strategies, enhancing service reliability and operational efficiency.

Moreover, the success of the system underscores the potential for broader applications within utility management and suggests that similar approaches could be employed to tackle other challenges within the energy sector. The adaptability and scalability of the model present opportunities for future research and development aimed at refining prediction algorithms and expanding their applicability to other regions and utility types.

In conclusion, the DSS developed through this research provides a robust tool for enhancing the resilience and efficiency of electricity distribution networks, offering significant benefits to utilities and their customers.

There are some limitations and challenges to this study: The first one is the accuracy of the AI-based OMS heavily relies on the quality and comprehensiveness of the input data. Incomplete or inaccurate data can lead to suboptimal predictions. Inconsistent data recording practices and the lack of standardized data formats across different regions or utilities can hinder the system's performance. The second one is processing large volumes of real-time data from various sources (e.g., weather data, sensor data) requires robust computational resources. High computational demands may lead to increased operational costs and necessitate the use of advanced hardware and cloud computing solutions.

Future research could explore the integration of more diverse data sources, such as real-time sensor data from smart meters, IoT devices, and advanced weather radar systems. This could enhance the accuracy and timeliness of outage predictions.

Expanding the system to cover different geographic regions and varying infrastructure types (e.g., urban vs. rural, underground vs. overhead lines) could validate the model's scalability and adaptability.

Developing predictive maintenance algorithms that not only predict outages but also suggest specific maintenance actions for network elements could further enhance operational efficiency.

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