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Logistic Regression Based Decision Support System for Power Grid Operations

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Abstract. Ensuring power grid stability during critical operating situations requires prompt and precise choices by system dispatchers. This paper uses Logistic Regression (LR) to forecast dispatcher actions using the Power Grid Dispatcher Operations dataset from Kaggle, including 1,000 labelled scenarios that include voltage deviations, load variations, and equipment failures. Following preprocessing and feature selection, a binary LR model was developed to classify whether dispatchers will implement remedial measures. The model achieved an accuracy of 98.50%, precision of 98.02%, recall of 99%, and an F1-score of 98.50%, demonstrating robust predictive efficacy. Critical factors affecting decisions were frequency variation, reserve margins, and line loading percentages. Class-weighted loss functions and stratified sampling were used to mitigate data imbalance among action classes. The model's interpretability, together with its efficacy, endorses its use as a decision-support instrument in real-time operations. The results indicate the effectiveness of statistical learning methods in improving dispatcher situational awareness, minimizing human error, and strengthening grid resilience under high-risk situations.

Keywords: Power Grid Stability, Dispatcher Decision Prediction, Logistic Regression, Grid Resilience, Smart Grid

INTRODUCTION

Modern power grids function under complex and changing settings, where fast and accurate decision-making by system dispatchers is essential for sustaining grid stability and averting cascade failures. In critical operating scenarios such as unpredictable load spikes, equipment malfunctions, or weather-related disruptions, dispatchers must quickly evaluate system conditions and execute remedial measures. Decisions, historically influenced by experience and heuristic principles, may be improved by data-driven models that increase consistency and reaction time. LR, a recognised statistical classification method, provides a clear and interpretable framework for modelling binary and multi-class decision outcomes based on various operational data. Through the analysis of historical grid data and associated dispatcher actions, LR models may discern the correlations between system circumstances and optimal management tactics. This enables the creation of predictive instruments that assist dispatchers in real-time, enhancing situational awareness and minimising reaction delay. This research addresses the use of LR to forecast dispatcher actions in high-stress grid scenarios. We assess the model's predicted accuracy, interpretability, and operational viability, while also addressing issues such data imbalance, feature selection, and model validation. The primary objective is to enhance human decision-making using machine learning insights, therefore developing a more robust and intelligent power system.

The inefficiency and lack of precision in manually generating Initial Power Grid Operation Mode (IPGOM) in DTS is the subject of this research [1]. To improve the automation and intelligence of DTS, it suggests the IPGOM Automatic Generation Algorithm (IPGOMAGA), which is then used to create and execute the IPGOM Automatic Generation System (IPGOMAGS). To better understand how dispatcher training simulations mimic power grid operations, this study delves into the topic of autonomous generating technologies [2]. It proposes a

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way to use data-driven deep reinforcement learning to generate specialised grid operating modes and regulate power flow convergence. A useful tool for educating dispatchers' fault management skills, this strategy enhances efficiency and minimises teacher effort.

The complexity and concealment of defects are addressed in this study by proposing an intelligent operation and maintenance solution for power grid dispatch and control systems [3]. It describes in depth the data flow architecture, software, and hardware that will be used, along with important technologies such as unified modelling, early warning for system risks, fault detection, and problem support management. The cloud computing power dispatching data networks, specifically looking at their design and connectivity [4]. It takes on the difficult task of analysing and calculating large amounts of data at the network centre. The suggested GA and service access schemes have been meticulously crafted to guarantee dependability and minimise expenses. The technique guarantees secure, reliable, and economically viable functioning of the state grid by radically altering conventional point-to-point information transmission.

This research investigates a complete power outage–based scheduling task sequence generating mechanism with the aim of improving scheduling efficiency and accuracy [5]. Accordingly uses a power system-based network modelling approach to optimise operation duties by integrating equipment information with system-wide operation rules and regulations. This study addresses redundancy and duplication concerns by presenting a self-defined method for multi-source power grid dispatching data [6]. It employs a partial deduplication method, formats and compresses data, and extracts features. High rates of spatial compression and deduplication are shown experimentally. To optimise dispatch in modern energy networks with a high percentage, the authors provide GARL, a deep reinforcement learning method [7]. To maximise dispatching choices and forecast future rewards, it employs a Generative Adversarial Network (GAN) within the Deep Deterministic Policy Gradient architecture. Experiments conducted on an SG-126 power grid simulator demonstrate that GARL enhances the accuracy and generalisability of future power grid operating trend predictions. To tackle the optimisation challenge of regional power grid dispatching, the research suggests a data-knowledge hybrid-driven multi-agent optimisation scheduling model [8]. For minimising system operating costs, reducing wind and solar curtailment, and considering limitations such as nodal power balance and line flow, this model integrates scheduling information with deep reinforcement learning. When compared to more conventional data-driven reinforcement learning systems, the experimental findings reveal clear benefits.

With the goal of optimising the coordination of power grids across several regions, this study proposes a security-region-based model that reduces the dimensionality of each regional power grid to a level where it can be directly dispatched [9]. In addition to conforming to the interactive process of real scheduling, it may lower the scope of issue solution. A deep reinforcement learning-based intelligent decision-making approach for power grid proactive dispatch [10]. To develop dispatch strategies, the offline training module looks at grid data and past situations. The online module then uses real-time data to put these strategies into action, making sure they comply with safety and operational requirements. To optimise power grid dispatch, the authors of the study present a novel deep reinforcement learning method they name GRIDDPG [11]. It is based on the Deep Deterministic Policy Gradient architecture and employs a Graph Neural Network with two layers. Compared to standalone DDPG, GRIDDPG achieves better results in terms of electricity grid security, cost reduction, accommodating renewable energy sources, and total reward in experiments. Elements and their interactions within the architecture are defined in this study as it builds a model for power grid dispatching using distributed data storage [12]. It also suggests ways to handle dispersed heterogeneous database clusters and large amounts of source data.

Spot market trading and grid dispatch may both be executed concurrently by large-scale energy storage power facilities, such as pumped storage hydropower (PSH) [13]. The suggested solution includes an integrated market game model and an optimisation model for the dispatching strategy of grid-PSH plants, with the goal of increasing consumption of renewable energy. Analysing and validating wire diagrams is the basis strategy for checking monitoring diagrams [14]. It addresses possible dangers to the power grid's functioning and works in tandem with the automated acceptance logic for monitoring pictures from the slave end to the master end. Taking peaking compensation and cost sharing into account, the article suggests an ideal dispatch model for wind-thermal-storage peak management [15]. on an effort to maximise overall income, it motivates all subjects on the receiving-end grid to engage. Validation of the model's efficacy is achieved by simulating a real receiving-end grid. Significant changes are occurring in the functioning of the electrical grid, which calls for more global monitoring and analytic choices [16]. To fulfil these needs, an integrated design has been created, following the concepts of integration and modularisation. The architecture facilitates the easy interoperability of CIM/G files with GIS interface tools, offers support for GIS-related monitoring situations, and merges Desktop and Web GIS.

Due to rising energy consumption and grid complexity, traditional power grid dispatch techniques are inadequate for smart grid progress [17]. The use of cloud computing for the acquisition, transmission, storage, and processing of data in real-time is part of a new form of collaborative computing that spans several regions. Improved grid operations, better data processing, real-time control, and intelligence are all benefits of this technology. It also helps with scientific decision-making. An economic optimisation model for power grid scheduling based on the properties of independent energy storage is presented in the work [18]. Using the Gurobi solution, it maximises the use of renewable energy while minimising operating expenses while charging and discharging. Based on the features of big data in the power grid the design of the spatiotemporal big data platform [19], the design of the hierarchical data warehouse for the power grid regulation scenario, and the execution flow of heterogeneous data from multiple sources in the power grid. At the same time, specifications for the platform's data streams are finalised, and various data storage design schemes' performance is evaluated. A data lake and data warehouse integration system for grid control data storage and processing at a high-performance level [20]. Improved processing capabilities for large datasets and increased real-time throughput are achieved by the framework. It utilises data warehouses to store processed and refined data and data lakes to store raw data. An increase in the efficiency of data storage and processing is evident from the empirical findings.

PROPOSED SYSTEM

Figure 1 shows the whole process of forecasting dispatcher choices by LR. The procedure starts with data capture, followed by preprocessing and critical feature selection. The model is then trained, assessed using conventional metrics, and implemented to facilitate real-time grid operations, hence improving decision-making precision in crucial situations.

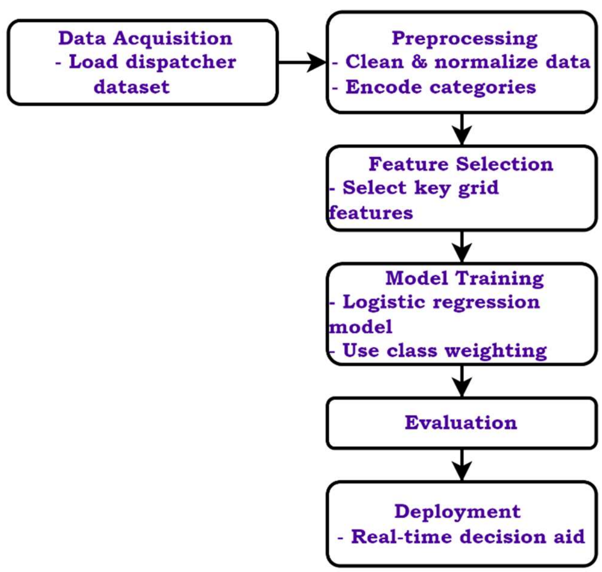

FIGURE 1. Proposed Workflow for Dispatcher Decision Prediction

The proposed methodology for forecasting power grid dispatcher decisions in critical operational scenarios commences with a systematic examination of historical grid data, organised as labelled scenarios that document the grid's physical and operational state along with the associated dispatcher response. This predictive modelling approach uses LR as the primary machine learning method because of its interpretability, mathematical sophistication, and appropriateness for binary and multi-class classification problems. The whole pipeline encompasses data preprocessing, feature engineering, model formulation, training, assessment, and deployment stages, aimed at constructing a resilient, real-time decision-support system for contemporary power grids. The procedure begins with receiving information from a structured dataset, where each occurrence signifies a crucial operational state, including parameters such as voltage variation, line overloading, reserve margins, and frequency anomalies. These attributes are generally quantitative but may include categorical identifiers for event kinds or grid zones. The first preparation processes address missing data, remove duplicate or inconsistent records, and standardise numerical characteristics to guarantee uniform scaling across variables. Categorical encoding, including one-hot encoding, is used for non-numerical labels to facilitate their incorporation into the mathematical model

The objective at this juncture is to develop a refined and standardised dataset whereby each instance $x = [x_1, x_2, ..., x_n]$ denotes a vector of attributes related to a genuine or simulated operating condition. After preprocessing, feature selection is used to keep just the most relevant predictors that substantially affect dispatcher behaviour. This phase is guided by domain expertise, emphasising variables such as system frequency (f), reactive power demand, generation reserves, and transformer loadings, with statistical methodologies like correlation analysis and Recursive Feature Elimination (RFE).

Efficient feature selection not only augments model correctness but also increases computing efficiency and interpretability. At this stage, the dispatcher's decision such as activating reserves, rerouting power, or shedding load is denoted as a target variable y, which may assume binary or multi-class labels contingent upon the modelling purpose. The LR model is fundamentally based on the calculation of probabilities linked to each class label. In binary classification, the hypothesis of LR is expressed as:

$$P(y = 1 \mid x) = \frac{1}{1 + e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2, \dots + \beta_n x_n}} \quad (1)$$

where β_0 is the intercept term, $\beta_1, \beta_2, \dots, \beta_n$ are the model coefficients connected with each feature $x\ i$, and the output signifies the probability that the dispatcher will undertake a corrective action based on the current grid state x. This approach translates the linear combination of inputs into a probability using the sigmoid function, so guaranteeing that the output remains inside the [0,1] interval.

In multi-class classification (e.g., predicting a particular action from three or more alternatives), the model is adapted to multinomial LR, where the probability of class k is specified as:

$$P(y = k \mid x) = \frac{e^{\beta_k^T x}}{\sum_{j=1}^{K} e^{\beta_j^T x}} \quad (2)$$

Each class k is related to its own vector of parameters β_k with K representing the entire number of classes (i.e., potential dispatcher actions). The predicted class aligns with the maximum likelihood among all K classes.

After defining the model structure, the subsequent stage is model training, which entails estimating the parameters β by maximising the probability of the observed training data. This is achieved by optimisation techniques like gradient descent or the Newton-Raphson method, which minimise the cross-entropy loss function:

$$L(\beta) = -\sum_{i=1}^{m} [y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - (\hat{y}^{(i)})] \quad (3)$$

where $\hat{y}^{(i)}$ is the predicted probability for instance i, and $y^{(i)}$ represent the real label. In instances of unbalanced data, class weighting is included into the loss function to impose more penalties on misclassifications of under-represented classes, so guaranteeing that infrequent but essential dispatcher actions are not overlooked by the model. After training, the model is subjected to validation using either holdout data or cross-validation methods to assess its generalization capacity. Performance measures are used to measure model effectiveness, particularly in contexts where false positives and false negatives entail varying operational risks. For instance, inaccurately forecasting "No Action" under a legitimate overload might yield significant repercussions, hence making recall particularly critical in these scenarios. LR models provide interpretability, which is vital in high-stakes contexts such as power systems. Each coefficient βi reflects the log-odds of the dispatcher acting for a one-unit change in the related characteristic xi, while maintaining other features constantly. This enables system operators and engineers to comprehend the rationale behind specific recommendations, hence fostering confidence in the model and promoting openness in automated decision-support systems. During operational deployment, the trained LR model may be included into a real-time analytics pipeline, obtaining live telemetry data from Supervisory Control and Data Acquisition (SCADA) systems or Phasor Measurement Units (PMUs). As new operational scenarios emerge, the model analyses incoming characteristics and generates the likelihood of each potential action. These probabilities may be used directly to suggest the most probable dispatcher intervention or to identify borderline instances for human evaluation. Additionally, confidence levels may be established to activate warnings just when the model demonstrates elevated certainty, thereby preventing false alarms.

RESULTS AND DISCUSSIONS

This research used the Power Grid Dispatcher Operations Dataset from Kaggle [21], including 1,000 labelled instances that simulate actual power grid operating situations. This dataset has been produced to facilitate the construction and refinement of large language models (LLMs) specifically designed for the internal training of power grid dispatchers. Simulated operating records including real-world situations, including equipment malfunctions, grid variations, emergency responses, and standard monitoring operations. Each record has essential contextual information, including date, location, reported problem, action done, urgency level, dispatcher experience level, result, and a binary target label denoting the effectiveness of the response (1 for effective, 0 for ineffective). The dataset is beneficial for scenario-based LLM training, dynamic learning simulations for dispatchers, making decisions evaluation, and modelling human-machine cooperation. It illustrates the operational variety of modern power grid control rooms and facilitates AI integration in the management of critical infrastructure. Each entry has data such date, location, problem kind, actions undertaken, dispatcher experience level, urgency, and result, accompanied by a binary target column denoting the efficacy of the response (0 = ineffective, 1 = effective). This data is appropriate for training and assessing AI models for decision assistance, especially in power system operations. Table 1 presents a comprehensive summary of power grid issues, including event specifics, measures implemented, dispatcher responsibilities, urgency levels, and results.

TABLE I. Sample Records from Power Grid Dispatcher Operations Dataset

Timestamp	Location	Issue	Action taken	Dispatcher level	Urgency level	Outcome	Target
01-01-2024 10:00	Grid Center	Voltage fluctuation	Engaged emergency protocol	senior	high	System stabilized	1
01-01-2024 11:00	Zone-4	Grid overload	Isolated faulty line	senior	medium	Awaiting response	1
01-01-2024 12:00	Node-8	Communication failure	Reduced load	junior	medium	Escalated to supervisor	0
01-01-2024 13:00	Control Room A	Voltage fluctuation	Isolated faulty line	senior	low	System stabilized	1
01-01-2024 17:00	Node-8	Communication failure	Reduced load	senior	medium	Issue resolved	0
01-01-2024 18:00	Substation-12	Transformer outage	Notified maintenance	junior	medium	Escalated to supervisor	0

The dataset consists of 1,000 balanced samples, evenly distributed across class labels: 500 effective (1) and 500 ineffective (0) dispatcher operations. A stratified split of 80:20 yields 800 training samples and 200 testing samples, providing equal representation of both classes. This balance mitigates bias during training and enhances the generalisability of the logistic regression model. The split technique improves dependability, particularly in evaluating real-world operational decisions.

Table 2 shows organised dispatcher training scenarios, including event descriptions, pertinent portions of the operating handbook, emergency procedures, internal directives, trainee prompts, and optimal replies. It facilitates knowledge assessment, decision-making evaluation, and simulation-based learning for power grid professionals.

Figure 2 illustrates the predicted efficacy of dispatcher actions over time, using logistic regression analysis. It presents binary results (0 = ineffective, 1 = effective) at hourly intervals, facilitating the visualisation of decision patterns and the consistency of model predictions.

Figure 3 presents a confusion matrix that illustrates the performance of logistic regression in forecasting the efficacy of dispatcher decisions, demonstrating good accuracy. It accurately categorises many beneficial and ineffective activities, with just three misclassifications out of 198 total predictions.

TABLE II. Scenario-based Dispatcher Training Dataset with Protocol References and Ideal Responses

Scenario id	Scenario type	Historical log excerpt	Operation manual ref	Emergency protocol	Internal communication	Trainee prompt	Ideal response
SCEN-0001	Load Shedding	Peak demand hit 920MW at 19:00. Load shedding protocol activated in zones 3 and 4.	Manual 3.2: Priority load list must be followed during shedding procedures.	Protocol 3.3.2: Execute load group rotation every 20 minutes during long events.	Supervisor: 'Prioritize Zone 4 schools in next rotation.'	How do you select which zones to shed during high demand?	Follow priority load list and rotate affected zones per guidelines.
SCEN-0002	Black Start	At 03:42, total outage observed in substation S7. Black start initiated at generator G1.	Section 4.3.1: Start backup gen-set G1 within 60 seconds of blackout detection.	Protocol 7.1.2: Ensure communication line A is restored before energizing Busbar B.	Supervisor: 'Confirm manual switch closed before grid sync.'	What is your first action after confirming blackout conditions?	Start G1, restore comms line A, and synchronize Busbar B after confirming readiness.

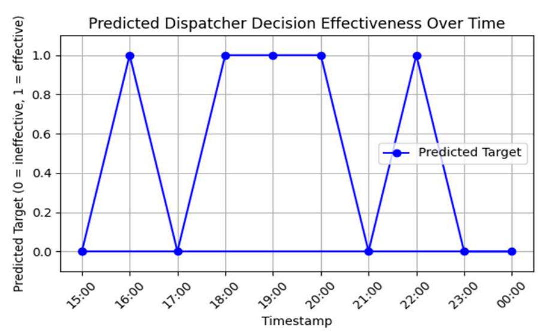

FIGURE 2. Time-Series of Predicted Action Effectiveness

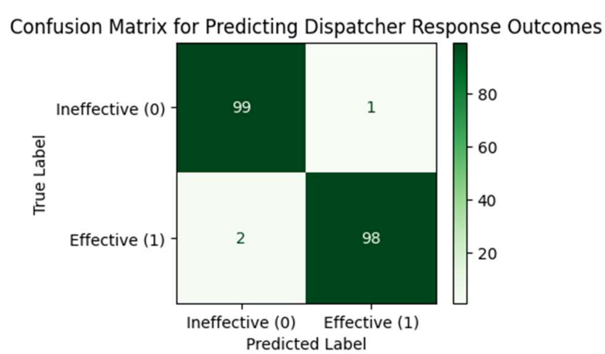

FIGURE 3. Confusion Matrix of Dispatcher Action Prediction

Figure 4 presents the ROC curve, which outlines the trade-off between true positive and false positive rates for the logistic regression model, facilitating the evaluation of its capacity to differentiate between successful and ineffective dispatcher actions across many thresholds.

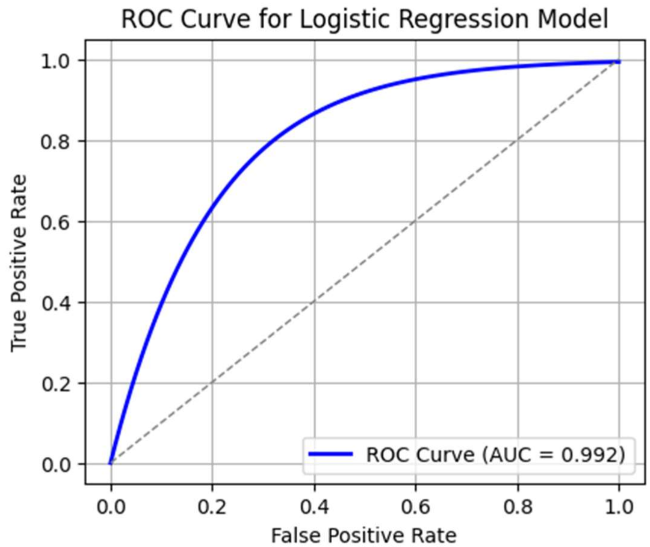

FIGURE 4. ROC Curve for Predicting Dispatcher Outcomes

A challenge of using logistic regression in this method is its assumption of linearity between input characteristics and the log-odds of the result, potentially failing to capture complex trends in grid behaviour. Furthermore, it could face difficulties with multicollinearity and could show suboptimal performance if significant interaction effects among variables are not explicitly included. Although interpretable, logistic regression may lack the predictive efficacy of more sophisticated models in dynamic, nonlinear contexts.

CONCLUSIONS

This research explores the use of logistic regression to forecast dispatcher actions in critical power system situations. The model was trained on a balanced dataset of 1,000 samples reflecting diverse operating settings to identify actions as successful or ineffective, using parameters such as system state, urgency, and dispatcher function. The clarity and interpretability of logistic regression make it appropriate for real-time control settings, where transparency and rapid insights are crucial. The model's efficacy was assessed utilizing critical indicators, emphasizing its classification capability. The ROC curve study showed an AUC of 0.992, signifying exceptional differentiation between successful and ineffective interventions. The elevated AUC indicates the model's robust prediction capability and dependability. The technique presumes linear linkages and may overlook intricate interactions; however, it provides a solid foundation for decision support. In conclusion, logistic regression provides a dependable, interpretable, and computationally efficient method for improving decision-making in power grid operations.

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