Deferred Supplier Energy Amount Prediction Using Neural Network based on Switching Strategy for Resilient Smart Grid

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***Abstract*—With the rapid growth in population and economy, the global demand for electricity has increased significantly. To ensure that electricity is efficiently distributed to households and industries and minimize power losses, the adoption of smart grid technology has become essential. Smart grids offer the potential to reduce power losses during the distribution process and improve the overall efficiency of the electricity distribution system. Machine learning techniques have been successfully implemented to efficiently distribute power among various entities and satisfying customer demands. In the present work, several machine learning algorithms and MLP neural network have been deployed for predicting the amount of energy carried over to next period. The experimentation results highlighted the superiority of the MLP neural network algorithm, which outperformed the other state of the art machine learning algorithms yielding 0.998866 of R-squared and 44.228105 of RMSE. Moreover, we aim to introduce a distribution planning approach that fosters collaboration among electric distribution centres to effectively optimize the logistics of energy flows while minimizing energy deferment.**

***Index Terms*—Machine learning Algorithms, multilayer perceptron neural network, deferred supplier energy amount prediction, regression, smart grid.**

I. Introduction

The electrical power system is on the cusp of transitioning towards the next generation Smart Grid (SG) system, a topic that has garnered significant attention within the research community [1]. By integrating information and digital communication technologies with power grid systems, the SG enables bidirectional communication and power flow, which can improve the security, reliability, and efficiency of the power [2]. SG solutions aim to calculate the optimal generation, transmission, distribution pattern and store power system data. All this data is used to create efficient decisions based on certain cases [1]. In addition, the availability and expansion of big data in the SG system has sparked a growing interest in the application of machine learning (ML) concepts. These concepts offer effective ways to process and analyze the large volumes of data, presenting an opportunity to enhance efficiency, quality, and productivity. Recently, researchers have begun to pay special attention to SG systems. The SG faces attack detection challenges that are tackled through statistical ML methods. The goal is to classify measurements as either secure or attacked, depending on different attack scenarios observed in batch or online settings [3]. Reference [4] compared four classifiers: Logistic Regression (LR), Random Forest (RF), Gradient Boosted Trees (GBT), and Multilayer Perceptron (MLP) neural network for detecting instability source. The best prediction results are achieved with MLP (93.8%). Through the use of ML algorithms, the smart grid can predict grid stability under dynamically changing customer requirements and collect real-time consumption data through various sensors, thus avoiding grid failures. The authors of this study applied several ML algorithms such as LR, Decision Tree (DT), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Naïve Bayes (NB), RF, and K-Nearest Neighbour (KNN) to predict grid stability using the freely available smart grid stability dataset on Kaggle. Their findings showed that the SVM algorithm produced the most accurate result [5]. The article [6] discussed the importance of accurate electric load forecasting for power companies and the challenges in developing and selecting accurate time series models. The research proposes a ML approach using a Long Short-Term Memory (LSTM) based neural network. The results of the study showed that the LSTM-based model outperforms a ML model. With SG, efficient load management during peak times is crucial, and dynamic pricing policies can encourage customers to change their consumption patterns. However, determining the optimal pricing policy is a challenging task due to the uncertainty of electricity consumption. To address this problem, the study proposed a deep contextual bandit algorithm that uses a deep neural network to learn the context and associated rewards. The simulations showed that the proposed algorithm improves the system's reliability, reduces energy costs, and controls the power system's ramp rate [7]. The SG has emerged as a reliable and self-healing electrical system that can adjust to changing customer requirements. ML plays a crucial role in maintaining grid stability by predicting and avoiding breakdown situations. In this study [8], the authors utilized various ML algorithms to estimate grid stability using an open-access dataset from Kaggle. They and achieved an accuracy of 97.9% in load prediction using the Bagging classifier algorithm. The electric grid is an essential component of the power supply system. However, with the increasing demand for power, there is a need to manage it efficiently. To predict the stability of the SG network, this study conducted a novel Multidirectional Long Short-Term Memory (MLSTM) technique, which outperforms other popular Deep Learning (DL) approaches such as Gated Recurrent Units (GRU), traditional LSTM, and Recurrent Neural Networks (RNN) [9]. In the SG, a customer has the option to either use energy from the grid or sell their own energy back to the grid. To maximize profit based on the current electricity selling price, a smart home with a rooftop Photovoltaic (PV) system needs to predict the amount of energy generated by the PV system using a MLP based PV forecasting method for PV systems in smart homes. The proposed algorithm's performance is evaluated using cross-validation and testing with real-world PV data, demonstrating its high accuracy and lightweight nature [10]. Hasan and al. conducted a system for detecting electricity theft in SG using a combination of a convolutional neural network (CNN) and a LSTM architecture [11]. A LSTM recurrent neural network based framework for short-term load forecasting of individual electric customers was introduced by Kong and al. in the context of a more intelligent, flexible, and interactive power system with higher penetration of renewable energy generation. [12]. Rouzbahani and al. considered an efficient electricity theft detection algorithm using an Ensemble Deep Convolutional Neural Network (EDCNN) for SG, which rely heavily on Information and Communications Technology (ICT) and smart meters to manage the network [13]. The application of Artificial Intelligence (AI) and its subset, ML algorithms, can play a crucial role in predicting issues within the SG system which help in taking precautionary measures [2], thereby enhancing the security, reliability, and efficiency of the SG. In this work, the most important challenge, predicting the amount of energy carried over to the next period, is considered because it allows meeting customer demands without the need of the amount of energy not delivered in the previous period. By accurately predicting the deferred supplier energy amount, SG systems can better manage their energy supply and demand, and thus ensure that energy is delivered to customers on time and in the right amount. This approach can lead to increase customer satisfaction and minimize the deferred supplier energy amount to the next period, ultimately contributing to more efficient and effective energy management in SG systems. In summary, the main contributions of this work can be highlighted as follows:

- Comparative analysis of the performance of ML algorithms implemented on SG dataset against a DL based model for predicting the deferred supplier energy amount. The results highlighted the superiority of the DL based model, which outperformed the ML algorithms.
- Optimization of energy flow logistics while minimizing energy deferment.
- Implementation of a distribution planning approach that encourages cooperation between Energy Distribution Centers (EDCs) to efficiently fulfill customer demands as well as reducing energy deferment.

This study proposes a coupling between stochastic modelling, optimisation and prediction tools to propose a resilience strategy for energy distributors by creating a connected network between distributors. This is a new proposal to cope with the era of ever-increasing energy consumption which may be more limited in some areas than in others. The rest of the paper is organized as follows: Section II describes the production and distribution problem we will deal with in this paper. Proposed method for predicting deferred supplier energy amount is carried out in section III. Section IV focuses on results and discussion which show the role of ML algorithms in SG. Section V puts forward EDCs as a planning method capable of handling the customer demands and highlights its capabilities in minimizing the deferred supplier energy amount to the next period. Finally, the conclusion is drawn in section VI.

II. Problem description

Due to the scarcity of energy, it is imperative that we meet the needs of customers, given the significant importance of energy. As a result, we develop a distribution model for energy from a primary renewable energy source of a single machine M producing energy to meet fluctuating demands over a time horizon H, divided into N periods of duration W. To guarantee a satisfaction rate A to consumers during each period k, we call on an additional energy supplier to supplement the missing quantities and ensure this satisfaction rate. The supplier energy amount can be carried over from a period k to a period k+1 if the energy demand in period k can be satisfied by the output of the main renewable energy source in period k and the quantity supplied by the supplier previously in period k-1. The problem is illustrated in Fig. 1.

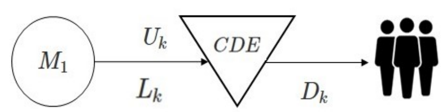

Figure 1. Problem description

Our objective is to minimize the deferred supplier energy amount that is carried over to the next period, for all periods k in order to optimize the logistics of energy flows.
The main decision variables, cost coefficients and parameters associated with the problem at hand are listed below:
A: The desired satisfaction rate.
H: The planning horizon.
U_k: the amount of energy delivered to the period k.
L_k: the amount of undelivered energy in period k-1 and carried forward to period k.
EDC: the energy distribution center necessary for the reception and delivery of energy functioning as a logistics platform in Cross-Docking.
S_k: the amount of energy present at period k in the EDC.
S_{sc}: the cost of managing the amount of energy collected in the EDC.
C_l: the cost of energy delivery.
α: probabilistic index (related to customer satisfaction).

$$\min_{L_k} \sum_k U_k * C_l + \sum_k L_k * C_l + \sum_k S_k * C_{sc}$$

Subject to:

$$L_{k+2} = D_{k+1} - U_{k+1} + L_{k+1} \qquad k = 0, 1, \ldots, N-1 \quad (1)$$

$$\text{Prob}[D_{k+1} \geq 0] \geq \alpha \qquad k = 1, 0, \ldots, N-1 \quad (2)$$

Constraint (1) depicts the deferred supplier energy amount. The constraint (2) imposes the service level demand for each period as well as a lower bound on inventory variables so as to prevent stockouts.

III. Proposed Method

In order to optimize the quantity not delivered and carried over to the next period, we propose the following approach:

- Use of regression models to predict the quantity carried forward.
- Propose a solution allowing the minimization of this predicted quantity .

The work-flow of the proposed model for predicting deferred supplier energy amount is depicted in Fig. 2. Python is used for making prediction. The methodology involves several steps, which can be summarized as follows:

- Generate a SG database.
- Preprocess the dataset using the StandardScaler method for normalization and label encoding for data transformation.
- The preliminary analysis of selected features.
- The dataset is then split into training and testing data.
- Multiple ML algorithms and MLP neural network are trained on the dataset and assessed using various metrics.

As presented in Fig. 1, the first part consists on collecting data. The number of samples from the dataset is equal with 10000 and the number of features is equal with 11. The features have numerical and categorical values. In Table I are summarized the main numerical and categorical characteristics of the dataset used in experiments. This data is used to train and test ML models as well as MLP neural network.

In the second step, the data are preprocessed, including data normalisation and label encoding to enhance data quality and also the performance of the ML algorithms. From the statistics about the dataset, different continuous features have very large range and deviations, which may create problem during model fitting. Add to that, many features have categorical values that ML algorithms cannot handle them directly. So, before we use this data in model building process, we normalize the continuous variables and encode the categorical features. To study the quality of the selected features, Fig. 3 summarizes the numerical and categorical features correlations to the target variable L(k+2). Besides this, a correlation of -0.52 between temperature and season indicates a moderate negative relationship between these two variables. This means that an increase in temperature is generally associated with a decrease in the probability of being in the winter, spring or fall. However, this relationship is not a strong one, as the correlation coefficient is not close to -1.0, and there is still considerable variability in the data. As shown in Fig. 3, D(k+1) is strongly correlated to the target variable, followed by U(k+1). So, they are the two most important variables in determining the deferred supplier energy amount L(k+2).

Table I
Experimental dataset features description.

Feature	Description
D(k+1)	The customer's demand
U(k+1)	The delivered amount in period k+1
L(k+1)	The not delivered amount in the period k and carried over to the period k+1
L(k+2)	The not delivered amount in the period k+1 and carried over to the period k+2. It is our target feature.
Temperature	The temperature at that period
Electricity price	The unit price of electricity
Day type	If the day was a holiday or not
Day week	The day of the week when the delivery took place
Customer type	The type of customer (residential or industrial)
Season	The season in which the delivery took place (winter, summer, spring or fall)
Energy source	The type of customer (renewable, nuclear or fossil)

After preprocessing the dataset and studying the quality of the features, 70% of the data which is called training data has randomly allocated to train the models, and the remaining 30% that is namely testing data was used for testing. The training data consists of 7000 rows and 11 features while the testing data includes of 3000 samples with 11 features. After, experimentations are carried out on SG dataset, fed to various classifiers like MLP neural network, XGBoost, RF, GBDT, DT, Linear regressor, Lasso regressor, SVM linear and KNN. Then, we estimated the target variable using these regression models that were tested on the test dataset. The last part consists on evaluating the performance of regression models according to certain metrics. The below metrics which are used to evaluate the prediction error rates and model performance are:

- R-squared R^2 (Coefficient of determination) represents the coefficient of how well the values fit compared to the original values. The value is from 0 to 1. The higher the value is, the better the model is.
- RMSE (Root Mean Squared Error) is the error rate by the square root of MSE (Mean Squared Error). The MSE represents the difference between the original and predicted values extracted by average the absolute difference over the data set.

IV. Results and Discussion

In this section, we present the experimental results obtained from various regression models trained on the same dataset including MLP, Extreme Gradient Boosting (XGBoost), RF

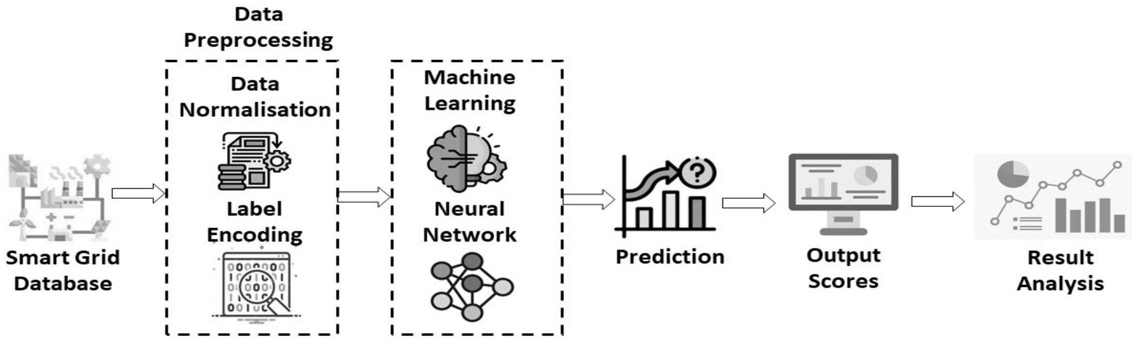

Figure 2. Proposed methodology

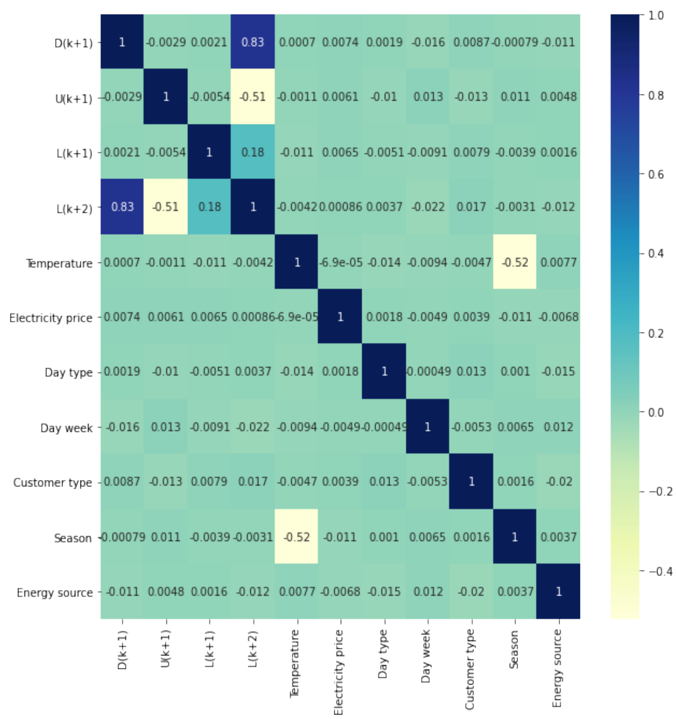

Figure 3. Heatmap features

regressor, Gradient-Boosting Decision Tree (GBDT), DT regrssor, Linear regressor, Lasso regressor, SVM linear and KNN regressor. We compare and contrast these models in order to select the most effective one based on the results obtained from the same dataset. Our evaluation of the experimental results will be based on two metrics, namely R^2 and RMSE. The Table II lists the nine regression models with the R^2 and RMSE values in the descending order of R^2.

From Table II, the analysis provides evidence that MLP algorithm provided the best results, followed by the XGBoost algorithm, RF regressor, GBDT and DT regressor. Linear, Lasso regression algorithms and SVM Linear algorithms results were quite close. The KNN regressor gives the least optimal result.

Table II
COMPARISON TABLE FOR ALL THE REGRESSION MODELS USED

Model	R^2	RMSE
MLP	0.998	44.228
XGBoost	0.996	83.014
RF Regressor	0.994	101.175
GBDT	0.991	122.983
DT Regressor	0.989	135.359
Linear Regression	0.968	231.483
Lasso Regression	0.968	231.503
SVM Linear	0.964	247.559
KNN Regressor	0.921	367.666

In Fig. 4, we also compare the performance of all the models using the R^2 and RMSE metrics for the ease of comparison. The best performing model is MLP with the highest R^2 and least RMSE. But even the XGBoost, RF regressor, DBDT ant DT regressor are also not far behind with respect to the metrics. Hence, we find that MLP neural network is the most efficient and provide the most accurate result. In order to minimize the predicted value, we will resort to use a distribution planning as discussed in the next section.

V. THE ROLE OF ENERGY DISTRIBUTION CENTERS (EDCS) IN MINIMIZING ENERGY DEFERMENT TO THE NEXT PERIOD

This section is dedicated to introducing a distribution planning approach that aims to implement a collaborative framework as shown in Fig. 5, enabling a EDC to reach out to other EDCs for assistance when needed, in order to fulfill customer demands with a high level of service while also minimizing the deferred supplier energy amount to the next period. we will propose a global N/N model for all EDCs that can collaborate with each other. The N/N EDCs must also meet the demand of each customer such as C1, C2 and C3 during a finite distribution horizon. We assume that demand may exceed the delivery capacity of each EDC. Collaboration

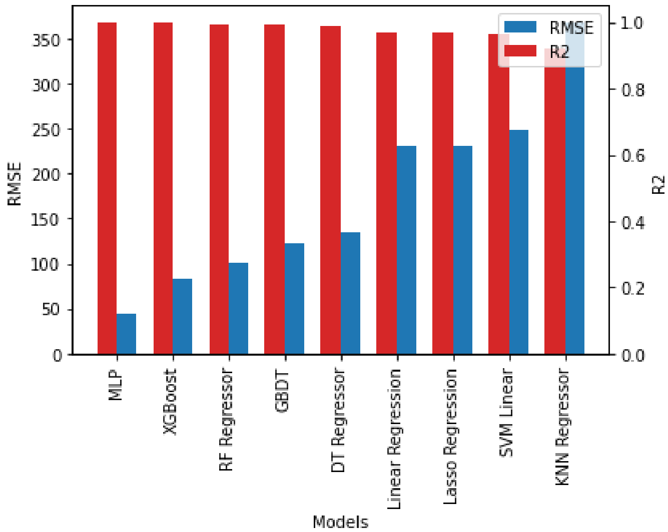

Figure 4. R^2 and RMSE scores

will occur when at least one EDC cannot satisfy all or part of the demand in the of the demand in period k. Unavailability can occur when the distribution rate is insufficient. As a result, the unavailable energy supplier may call the other EDCs to meet the entire the request. The subcontractor can be one of N/N possible EDCs. This approach is inspired by the reference to minimize the deferred supplier energy amount [14] and will be applied in the future as a solution to efficiently fulfill customer demands as well as reducing the predicted energy deferment.

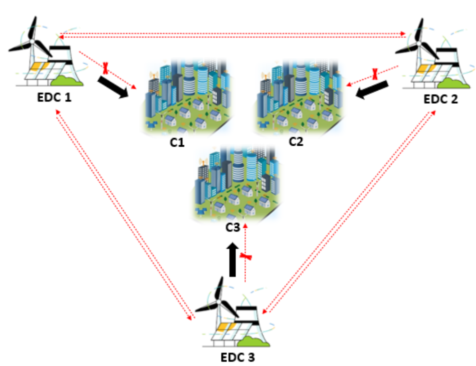

Figure 5. Distribution planning approach

VI. Conclusion

SG refers to a cyber-physical system that utilizes intelligent technology to efficiently distribute power among various entities. Power distribution to clients and satisfying customer demands are two of the most critical components of a SG system. In order to achieve this, ML techniques play a vital role in predicting the deferred supplier energy amount, which is important for managing demand and ensuring that the energy supply meets customer needs. This can help utilities adjust power generation and distribution accordingly. With the emergence of multiple ML algorithms, the ultimate challenge is to find the most effective algorithm to predict the deferred supplier energy amount. The experimental results proved that MLP neural network outperforms XGBoost, RF, GBDT, DT, Linear regressor, Lasso regressor, SVM linear and KNN in terms of R^2 and RMSE. It reached a coefficient of determination R^2 of 0.998 and 44.228 of RMSE.

As part of the future work context, we will implement a distribution planning approach that encourages cooperation between EDCs to efficiently fulfill customer demands while reducing energy deferment.

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