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Clustering-Based Energy Management of Residential Loads by using Artificial Intelligence †

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Abstract: Developing countries have witnessed a remarkable surge in the energy crisis due to the supply and demand gap. One of the solutions to overcome this problem is the optimal use of energy that can be achieved by employing demand side management (DSM) and demand response (DR) methods intelligently. Machine learning and data analysis tools help us create intelligent systems that motivate us to use machine learning to implement DSM/DR programs. In this paper, a novel DSM algorithm is introduced to implement DSM intelligently by using artificial intelligence. The results show an efficient implementation of an artificial neural network (ANN) along with demand side management, whereas the peak and off-peak loads were normalized to a certain range where a perfect agreement between supply and demand can be reached.

Keywords: DSM; ANN; orange canvas; pattern recognition; decision tree; load management

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1. Introduction

In electricity grids, electricity consumption and generation must be equal at all times. With a greater gap between production and consumption, there will be more chances of uncertainty and unreliability in the electricity supply. The intermittency will increase with the increase in renewable energy from PVs and wind turbines, which will decrease the guaranteed energy dispatch. In 2020, despite COVID-19, China inducted 117 GW of renewable energy [1]. Renewable energy generation has reached a record high at 29% of the total global electricity mix. Power plants are designed to meet the maximum demand required to construct high-capacity plants, adding more economical pressure on developing countries such as Pakistan.

To address this issue, it is necessary to understand the concept of demand response and demand side management. Demand side management programs motivate the consumers to actively participate in the electricity market [2]. According to the Federal Energy Regulatory Commission (FERC), demand response is the change in the electricity usage pattern that is achieved by influencing end-use customers by initiating different incentives in the electricity price [3].

There are two approaches to implementing demand response for any objective [4]. In direct load control, consumers receive credits for each event of direct load interruption. In the price-based approach, utility companies offer incentives to shut the load at peak load times [4]. Generation and distribution companies receive benefits in infrastructural expenses by using demand response to reduce the peaks [5]. A scheduling framework was presented in [6] that explains the optimal scheduling of residential loads with the objective of reducing electricity bills while maintaining comfort.

A home energy management system was presented in [7] that schedules the load on predefined priorities and maximum demand limits. An intelligent residential load management system (IRLMS) was presented in [8] that classifies schedulable loads (SL) and non-schedulable loads (NSL).

In this paper, we present artificial intelligence-based demand side management of residential loads. This paper is arranged as follows: Section 2 covers the methodology, where we describe the data collection, generation of patterns from collected data, pattern recognition using artificial intelligence and the algorithm. The simulation and results are presented in Section 3, and the conclusion is provided in Section 4.

2. Methodology

The methodology consists of the following sections: data collection, generation of patterns, pattern recognition and application of demand side management (DSM) to cater for the supply demand gap. More accurate results can be formulated by having more meaningful data. Therefore, data collection is the first step that later helps in compiling reliable results. Data were collected by using smart meters from an e-guard that can collect energy usage data of up to 12 different devices.

We conducted supervised learning, so our training data had a set target. A total of 70% of the data were selected for training purposes, while the remaining 30% of the data were used for testing purposes. The test data have no target because they were used to test the machine training accuracy.

ANN and decision tree algorithms are most commonly used for classification. We trained our machine using both algorithms and compared the results, where the ANN achieved superior results that led us to use the ANN for pattern recognition. The complete process of pattern recognition is shown in Figure 1.

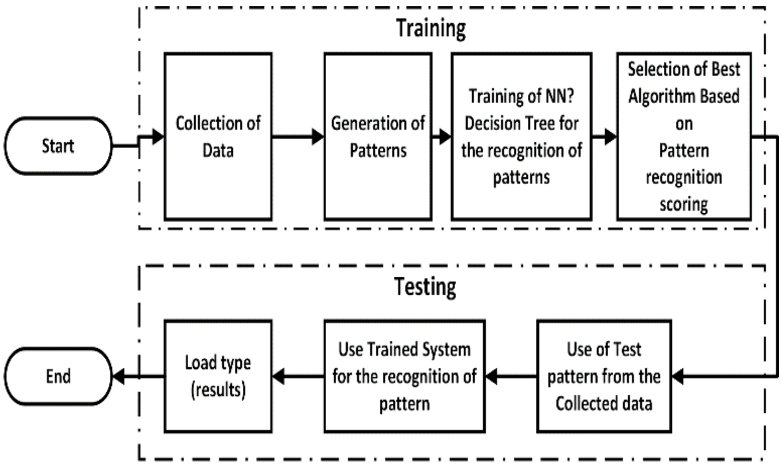

Figure 1. Load-type pattern recognition algorithm.

Demand side management starts after the recognition of patterns by using an artificial neural network. A smart demand side management algorithm is shown in Figure 2. Our target was to maintain the load within normal limits with the minimum discomfort to consumers, and with benefits for the supply company in peak load reduction and valley filling.

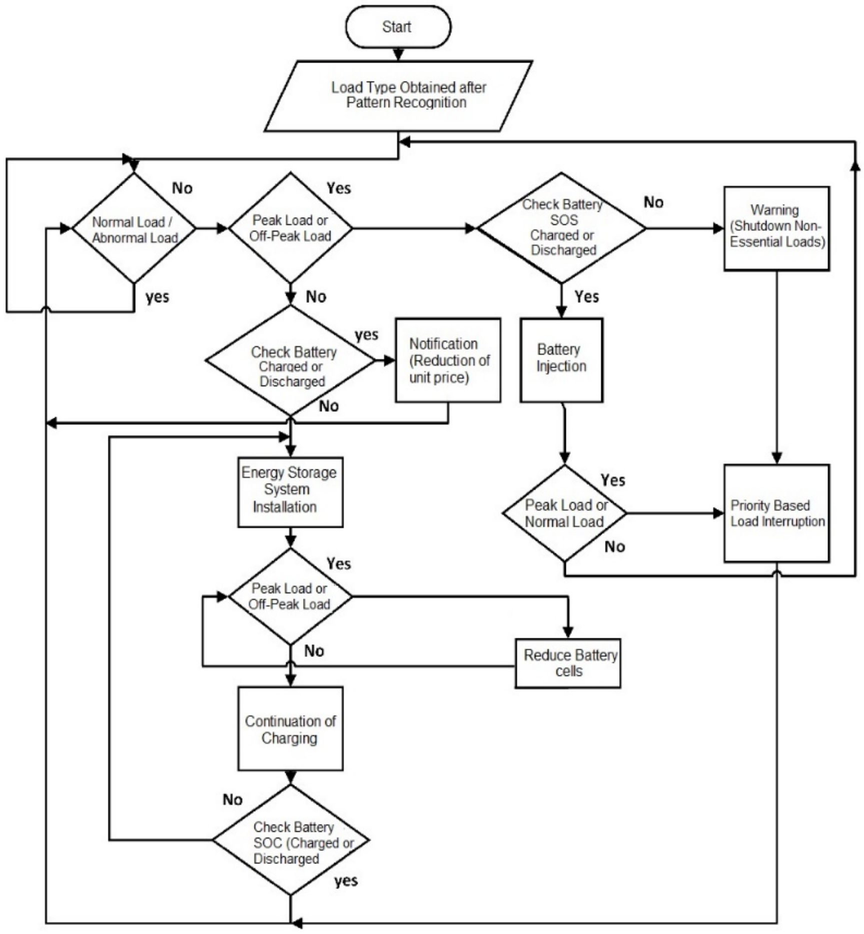

Figure 2. Load management algorithm by demand side management (DSM).

3. Simulation and Results

Based on the data collected from the demand side, we created the patterns of the load. The patterns were used for training and testing the model implanted in an orange canvas. As an example, a one-month pattern of the combined load of all houses is shown in Figure 3.

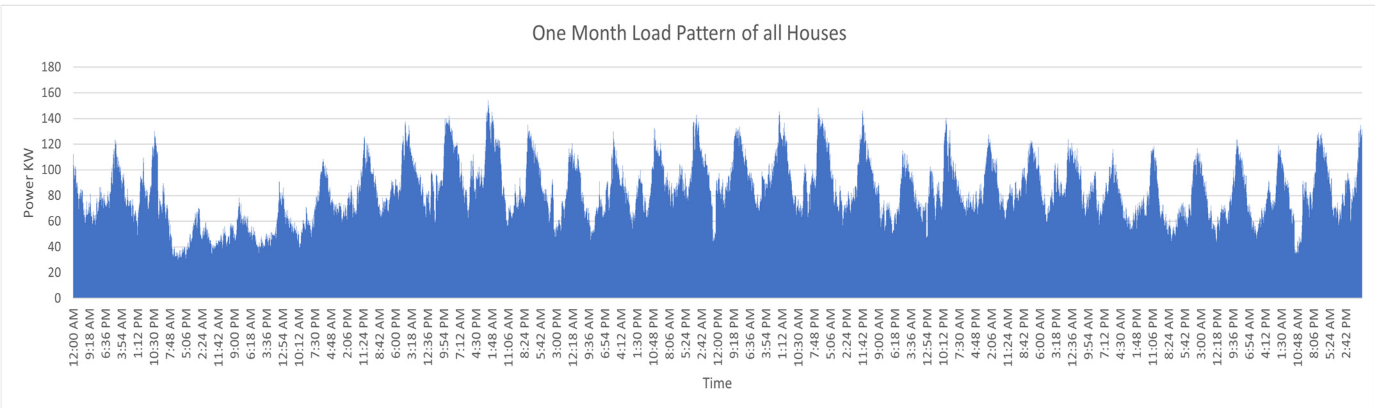

Figure 3. One-month load pattern of all houses.

The receiver operating characteristic curve (ROC) is the measure of sensitivity versus 1 [9]. It shows the performance of a classifier at all classification thresholds. Another factor to determine the classifier accuracy is the area under the curve (AUC). If a classifier has a higher AUC, it can be considered to be more accurate for classification. Figure 4 shows the ROC graph of the decision tree, and Figure 5 shows the ROC of the ANN.

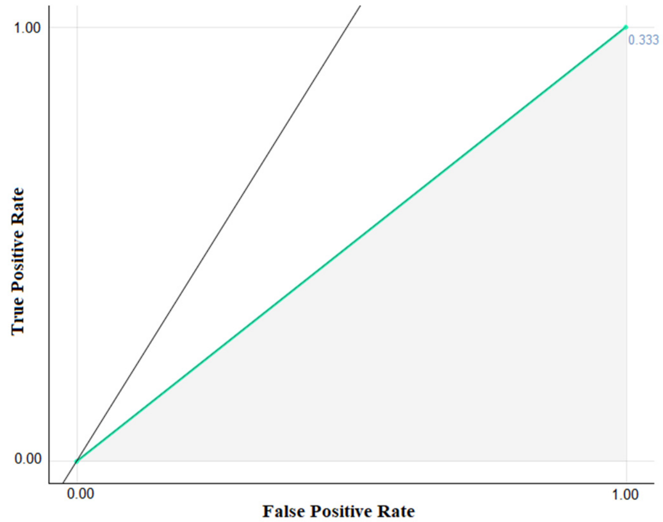

Figure 4. Receiver operating characteristic curve (ROC) of decision tree.

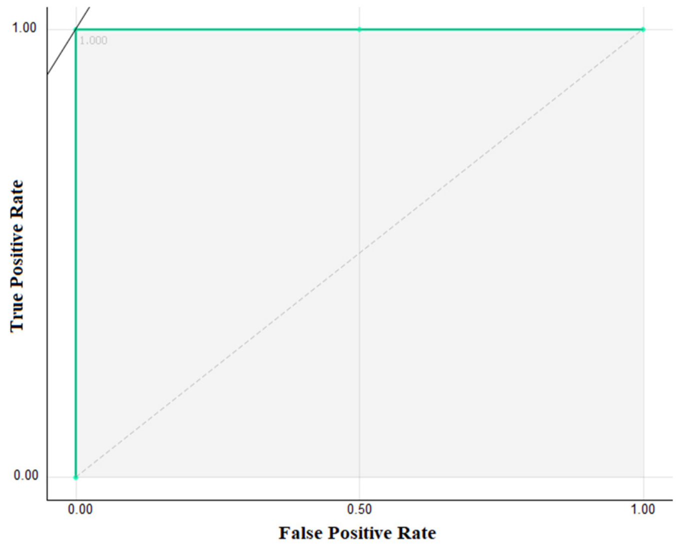

Figure 5. ROC of artificial neural network (ANN).

After training both systems, we obtained the prediction results. As we trained our system to classify normal, peak and off-peak patterns, the predictor should predict all three types of patterns accurately. Table 1 shows the test and scores of both the decision tree and ANN.

Table 1. Test and scores.

Model	AUC	CA	F1 Score	Precision	Recall
Decision Tree	0.5	0.3333	0.1666	0.1111	0.3333
ANN	1.0	1.0	1.0	1.0	1.0

On the bases of these training results, we found that an ANN is the most suitable form of algorithm to use for the classification of residential load patterns. Then, we used the testing data to test whether our machine predicted the load pattern accurately or not. Figure 6 shows the testing model of the ANN. Here, we inserted the test file, and the predictor classified the data pattern of the test file. We obtained patterns of the peak load, and our machine classified it accurately. Figure 7 shows the prediction result of testing.

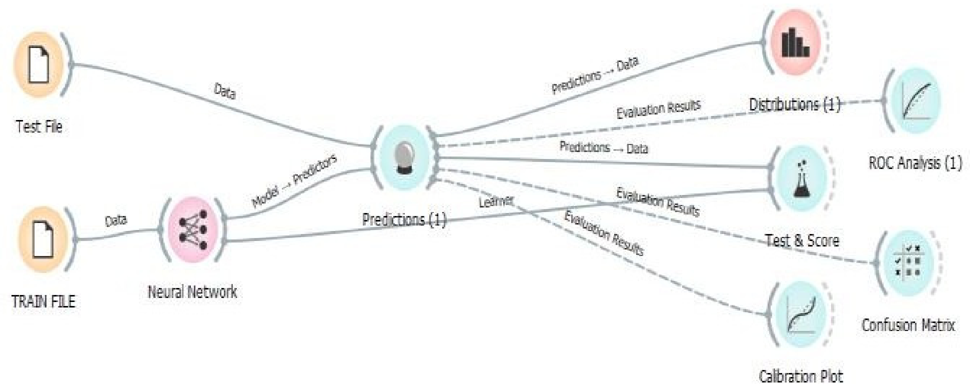

Figure 6. Testing model of the ANN.

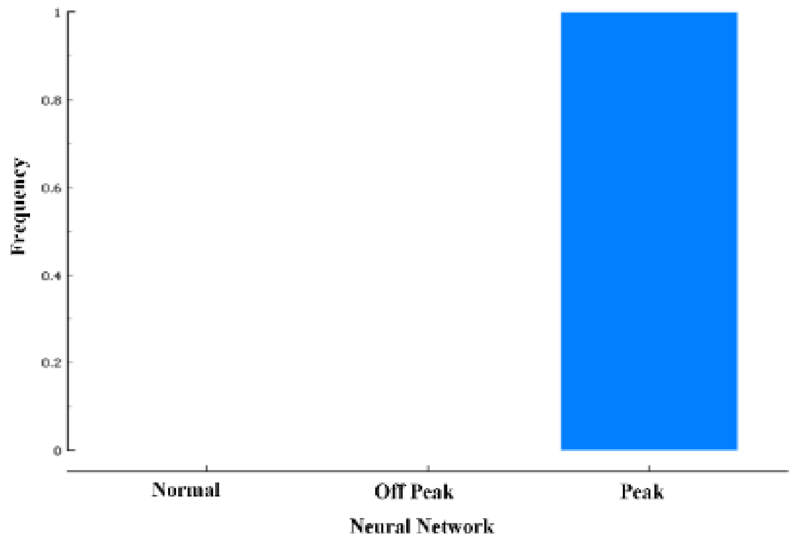

Figure 7. Prediction result of testing.

After the recognition of patterns obtained by the ANN algorithm, we applied DSM for load management. By using the algorithm shown in Figure 2, we normalized the off-peak load and peak load in the normal load range. It can be observed in Figure 8 that the areas above and below the normal demand range refer to peak and off-peak loads, respectively, which were later normalized by employing DSM.

From 9:00 p.m. to 1:00 a.m., the peak load occurred, and from 5:00 a.m. to 8:00 a.m., the off-peak load was obtained.

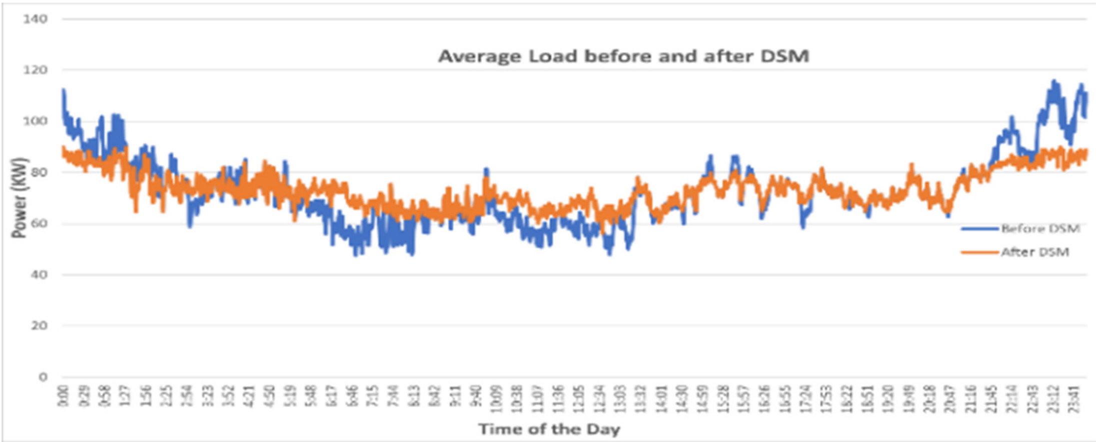

Figure 8. Average residential load before and after DSM.

4. Conclusions

The main crux of this research is the use of classified data generated from an ANN for demand side management. A novel smart DSM algorithm was introduced to normalize the load in peak and off-peak load intervals that used an energy storage system and priority-based load interruption technique to cater for the gap between supply and demand. The DSM-based algorithm was further tested on residential loads, and the results show an efficient normalization between the peak and off-peak loads.

Conflicts of Interest: The authors declare no conflict of interest.

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