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Neural Network Based Controller for Demand Response Management for a College Building

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Abstract: Energy management refers to the optimization of the energy system, one of the most intricate and significant technological inventions that we are aware of. While optimising has a lot of experience, the demand side is what drives the production and distribution of energy. Research and business are paying more attention to Demand Side Management (DSM) portfolio includes actions to enhance the energy infrastructure next to the consumer. It varies from enhancing energy efficiency by the use of superior materials over clever incentives in energy prices for specific use habits, increasing advanced real-time management of dispersed energy resources. In this paper, Neural Network based contreiler has been designed to perform the load balancing using a load profile of commercial college building dataset. The results obtained show the regression fir of 99.9% and error of 0.0005%.
Keywords: Demand Response management

I. INTRODUCTION

The fact that the energy distribution networks are now changing is a fact. The growing customer base and their requirements, as well as the more competitive market in which power providers must coexist, demonstrate the necessity for new smart distribution networks. The present network is under a lot of stress as a result of the multiple demands and concerns caused by problems with the environment, customers, markets, and infrastructure. Due to these challenges and demands, which are more important and urgent than ever, the network has expanded and improved its operations to include intelligent features with the help of quickly evolving technology.

The phrase "Smart Network" describes the evolution of transmission networks to make them more intelligent. The primary goals of these new intelligent energy distribution networks are meeting customer needs and maintaining the healthy profitability of power companies [1].

The term "Smart Network," though it was initially used much earlier, has become more common since the end of 2003. The operational aspects of the "Smart Network" or its technology components are frequently emphasised in definitions of the term. The point of convergence for everyone is the integration of digital communications and processing into the electrical grid, with data flow and management carried out by a centralised "Smart Grid" system. [2]

The term "smart grid" refers to an energy system that can intelligently integrate the activities of all users connected to it, whether they are generators or consumers, in order to provide an effective, reasonably priced, and secure electricity supply. A smart network makes use of innovative products and services as well as skillful network status monitoring [3].

The smart network links supply and demand by enabling producers and consumers to decide their operational demands more flexibly and sophisticatedly. Consumption at high costs, for example, can only happen for very good reasons, and consumers can control their consumption based on what they know about the present consumption price. On the other hand, producers with high degrees of flexibility can alter their sales prices to maximise their profits while also providing consumers with promotional periods based on the price of their power generation, expanding their advertising influence, and luring new clients.

II. DEMAND RESPONSE MANAGEMENT

Demand response management in the electrical industry plays a pivotal role in shaping the dynamics of energy consumption and grid stability. As the global demand for electricity continues to surge, traditional methods of power generation and distribution are being challenged to meet these escalating needs while ensuring environmental sustainability. Demand response management offers a sophisticated solution by allowing utilities and grid operators to actively manage and adjust electricity consumption patterns in real-time or during peak demand periods.

This involves engaging consumers to voluntarily reduce or shift their electricity usage when the grid is stressed or electricity prices are at their peak. By doing so, demand response programs alleviate strain on the grid, mitigate the risk of blackouts, and help maintain a delicate balance between supply and demand. The advent of smart grids and advanced metering technologies has revolutionized the way demand response is implemented. These innovations enable precise monitoring of energy consumption patterns at individual consumer levels, empowering utilities to provide timely incentives or signals for load reduction when required. This two-way communication between consumers and the grid enhances the overall efficiency of energy distribution, minimizes wastage, and contributes to a more sustainable energy landscape.

Moreover, demand response management aligns with environmental goals, reducing the need to tap into less-efficient and more polluting power sources during peak demand periods. This not only reduces greenhouse gas emissions but also promotes the integration of renewable energy sources into the grid, furthering the transition towards a cleaner and more resilient energy ecosystem. However, challenges remain, including consumer participation, regulatory frameworks, and technological integration. Overcoming these obstacles requires collaborative efforts between policymakers, utilities, technology providers, and consumers to establish effective demand response strategies that ensure grid reliability, cost savings, and reduced environmental impact.

III. DESCRIPTION OF THE RESEARCH WORK

In this study, a MATLAB/SIMULINK model of a three-phase power system was created. To meet the demand from the load, a neural network controller has been created. There have been two different voltage sources and two different load conditions. The controller is built in such a way that it will switch to a different three phase voltage source when the demand for power rises over 8000W. With the dataset covered in the next part, a neural network controller has been trained.

A. Data Set

Over the course of a year (8760 hours of data), this dataset contains the hourly load profiles for 24 representative facilities from various end-use industries, including industrial, commercial, and residential customers. Using our physics-based building simulator, an EnergyPlus-based tool capable of capturing the functions of the structures, the dataset comprises 18 simulated buildings that were tailored to the climatic zone of the state of New Jersey in the United States. Six reference structures were taken from the EnergyPlus reference structures, which are accessible to the general public and have been mentioned here. In distribution networks where each building is defined by its load profile, which represents its power consumption behaviour, this information may be used to simulate single-node as well as multi-node energy systems, including nanogrids, microgrids, and other integrated systems. In fact, this dataset enables academics and practitioners from across the globe to simulate their defined or modified test systems, enabling them to conduct a variety of studies addressing various engineering, economic, and environmental assessments has been used to train out neural network.

B. Threholding in the Dataset

The neural network has been desined as of regression application therefore to fit the dataset, thresholding has been done. A part of the thresholded data set is shown below

	A	B	C
34	9092	0	
35	10494	1	
36	9352	0	
37	10582	1	
38	9260	0	
39	10506	1	
40	9260	0	
41	9066	0	
42	10726	1	
43	9092	0	
44	10444	1	

datasettotrain

Figure 1 Thresholding applied over dataset

As can be seen, a numerical 1 is assigned when the power need is greater than 10,000 W, and a numerical 0 is assigned otherwise. Here, "1" indicates that the source is switched, whereas "0" indicates that the source is not switched.

IV. SIMULINK MODEL

The complete Simulink model of the three phase transmission line is shown below

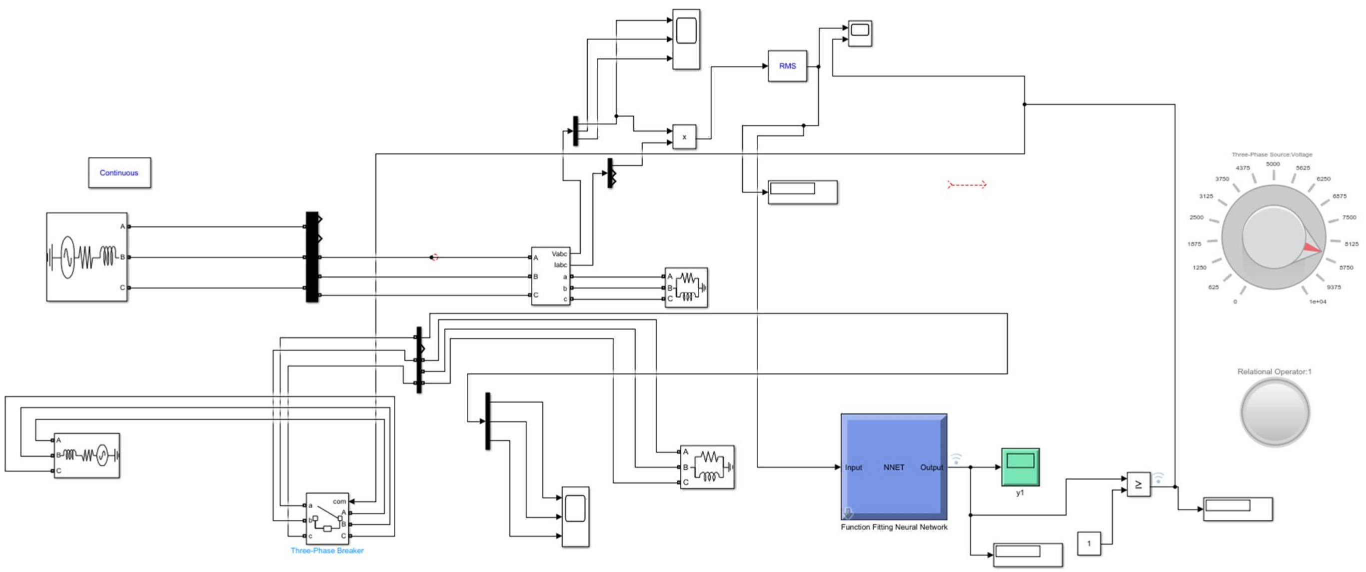

Figure 2 Complete simuling model of microgrid with the developed neural network controller

The model clearly shows that two unique three-phase AC sources were used to power two distinct loads. Here, one load is referred to as the major load, while the other is referred to as the secondary load. In the model, a knob has been employed to control the main circuit's voltage parameter. The power generated during the simulation may be altered using this knob. The neural network continually monitored the primary source's power, as seen in the model.

The three phase circuit breaker receives the output of the neural network controller. The controller provides a "HIGH" signal when the power rises beyond the threshold value since the displayed neural network was trained on the thresholded dataset. This high signal subsequently connects the secondary load to the secondary source. The primary or secondary load is being shown here using two different loads. The model includes a dashboard bulb that serves as a switching signal indication.

V. EXPERIMENTAL RESULTS

Simulation has been run for different time interval and the switching action is noted through an oscilloscope.

A. Result of the Switching

The controller has been seen to be functioning correctly in accordance with the prescribed thresholding. The graphic below displays the scope waveform.

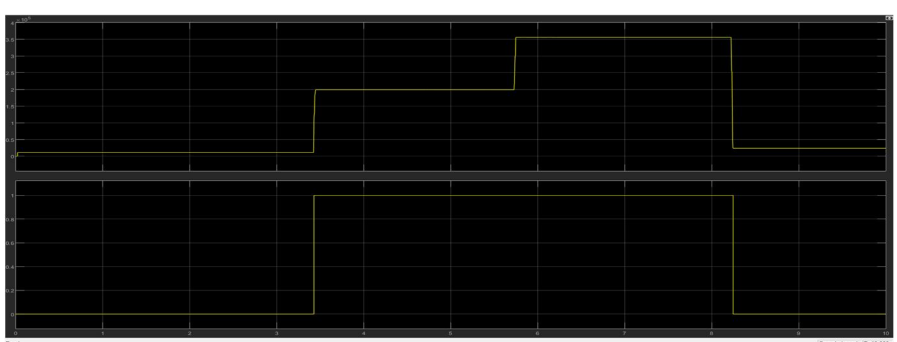

Figure 3 Switching waveforms

The load variation with respect to time is depicted in the top waveform using the dashboard knob settings. A switching signal at the bottom can either be 1 or 0, as determined by the dataset.

B. Analysis of the Trained Network

The error histogram of the trained network is shown below

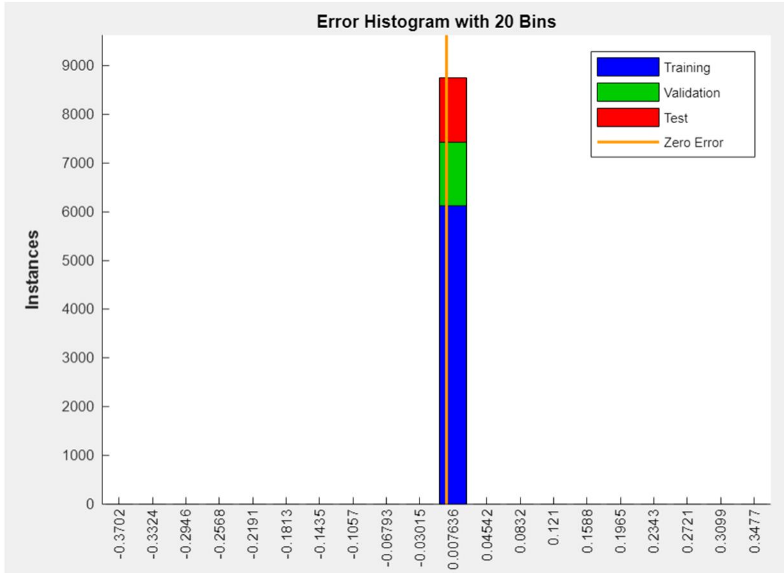

Figure 4 Error histogram

The regression fit of the Neural Network is shown below

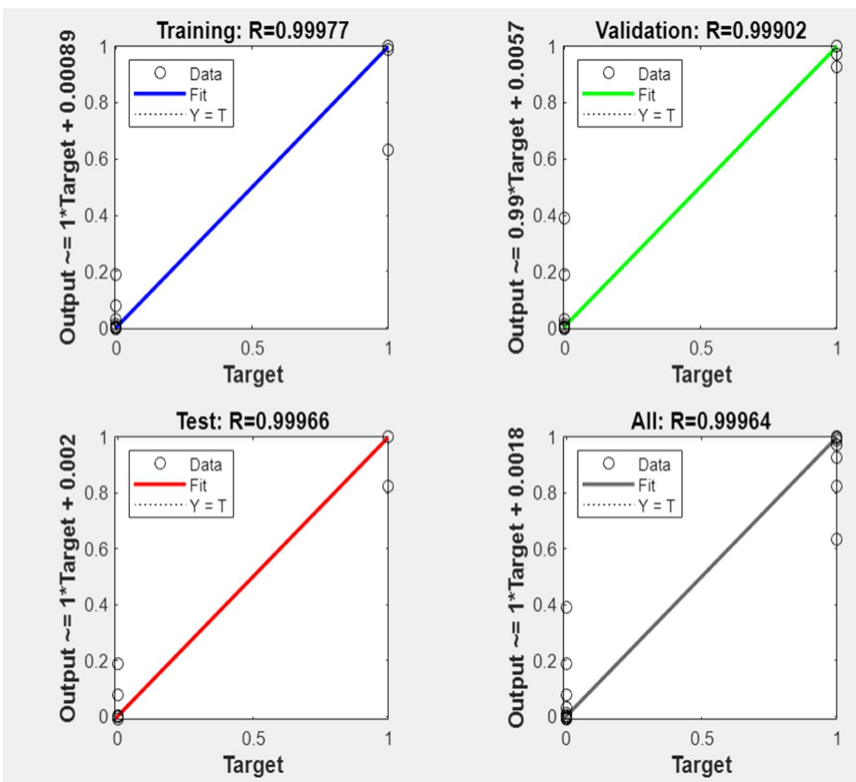

Figure 5 Regression fit

It can be seen that the regression of 99.9% has been obtained overall. The perfomace chart of the trained neural network is shown below.

The validation performance of the Neural network is shown below

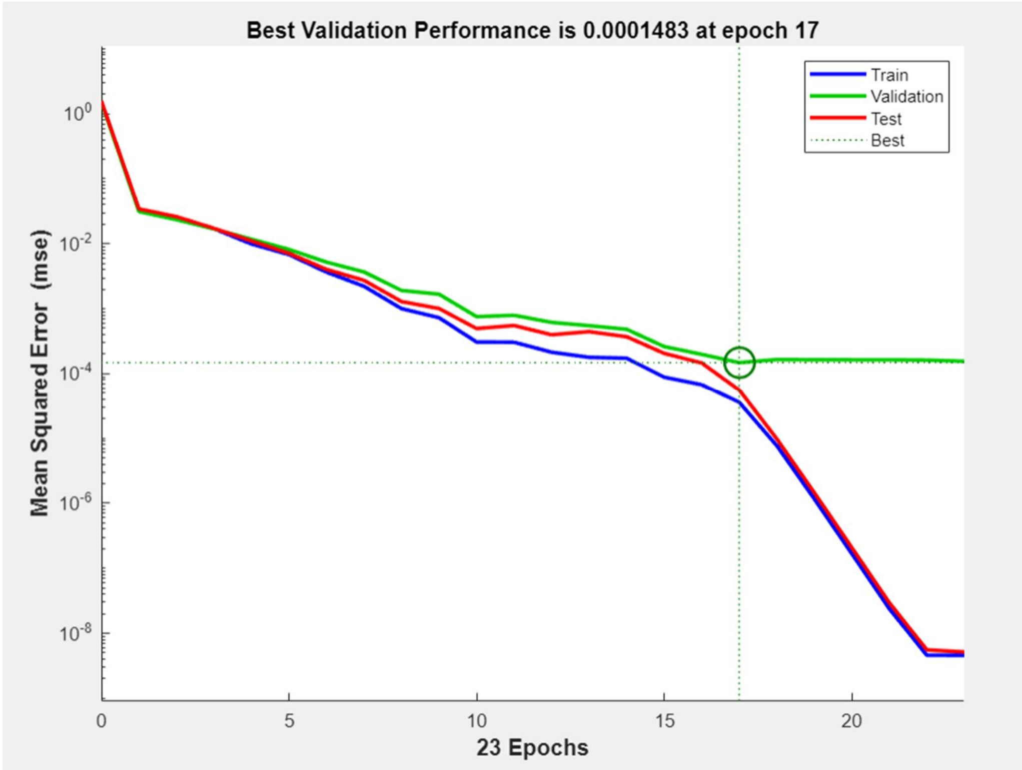

Figure 6 validation performance

VI. CONCLUSION

In this study, we balance energy generation and demand using the demand response management technique. Customers actively contribute to reducing demand during peak hours in a demand response management system in exchange for financial incentives. A microgrid has been simulated in this research utilising two different source and load combinations. The dataset of a commercial college building, which contains 8760 data items, was used to train a neural network. The switching was carried out by the neural network, and the outcomes are considered good. The largest error is determined to be 3.5e-5, and a 99.9% regression fit has been achieved. Different algorithms could be used in the future to boost neural network performance. taset.

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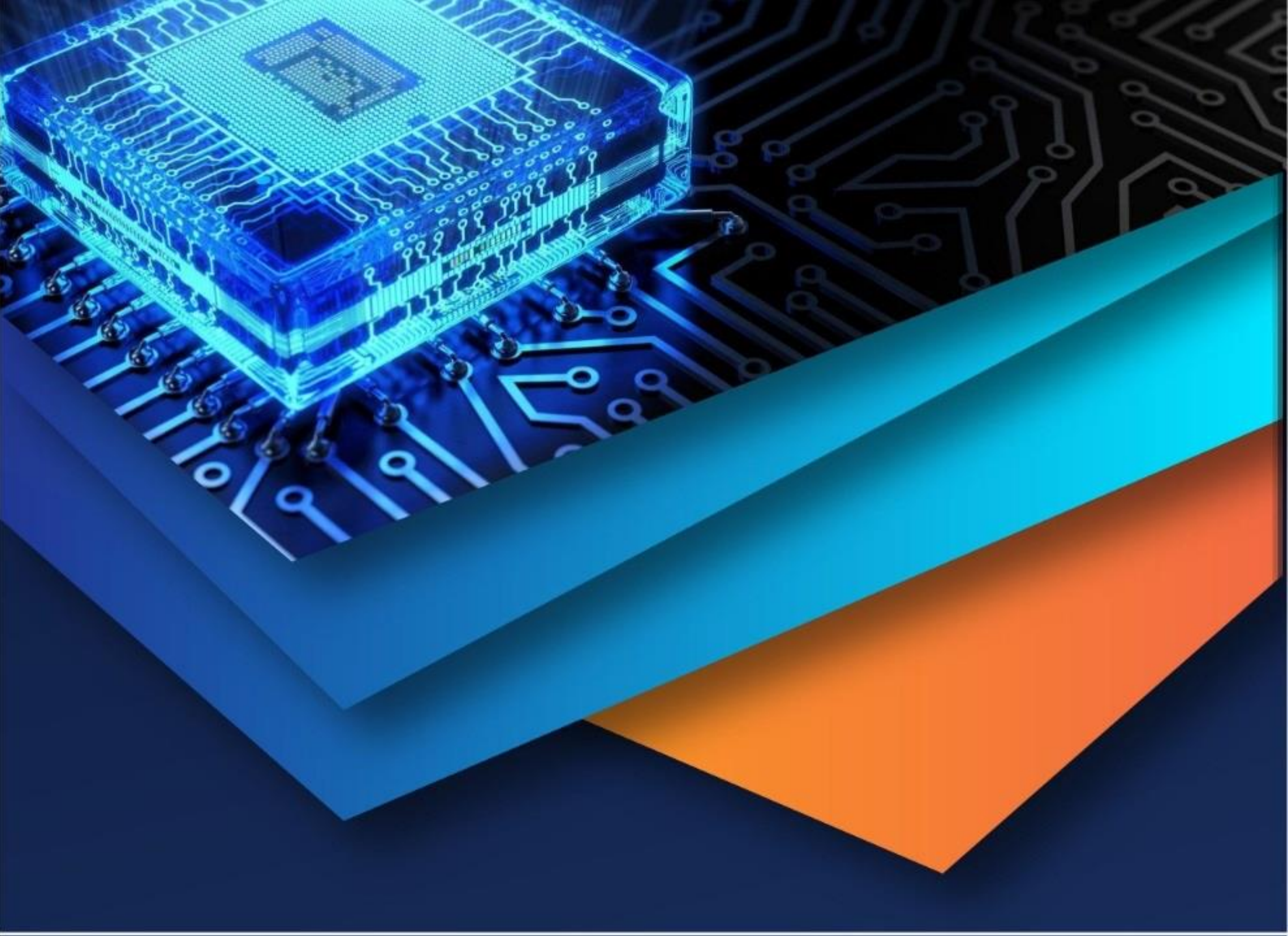

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