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Peak power management of residential building using demand side management strategies

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***Abstract*---**Peak power management is one of the demand-side management methods aiming at regulating energy usage throughout the day. This paper discusses peak load, which relates to a consumer's peak demand during specific hourly hours and how to manage it. Shifting loads from demand hours to non peak hours relieves pressure on utilities to meet demand and supply while also lowering the cost to consumers. The Peak Load Management Model offers a more effective framework for lowering peak loads and moving loads from peak to off-peak hours. A cascaded artificial neural network is utilised to construct a demand side management strategy for managing peak electricity in residential buildings in this paper. The peak load control model's results and discussion are highlighted in the simulation results and performance review.

***Keywords*---**cascaded feed, forward neural network, demand side management, green energy, load shifting, peak load management.

Introduction

Energy demand management actions aim to bring supply and demand closer to a near-optimal value, decreasing the need for additional infrastructure investment by utilities while also assisting end users in getting incentives for reducing peak power usage. Electric companies have experimented with several methods to regulate peak loads as demand for electricity rises. With the intention of balancing consumption and generation utilities were created. The highest electrical power consumption that has occurred over a specific time period is known as peak demand on an electrical system. Peak demand changes can happen on a daily, monthly, seasonal, or annual basis [1]. During peak hours,

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customers' energy use may exceed a utility's energy supply, resulting in substantial power outages, system instability, and blackouts. The residential sector is one of the most important factors driving peak demand [2]. Steady increase in residential loads, has a negative impact on a power system's stability and reliability. The research into residential peak load reduction strategies adds to international efforts to reduce energy usage.

When demand exceeds supply, Peak Load Management (PLM) allows a large number of customers to benefit from power limitations. Utilities can minimize component demand, increase grid efficiency, and increase grid resilience [5]. The action taken by utilities and/or consumers to change the load profile in order to reduce the total system peak load and meet demand during peak hours while maximizing the efficient use of valuable resources such as fuels for generation, transmission, and distribution capacity is known as electric load management. To manage the load at the customer's end, the load profile must be compared to the overall system demand.

i. Rescheduling of processes
ii. Charging energy storage devices during off-peak hours and using them during peak hours is the requirement of efficient load management.
iii. Self-generation of power.

Load management [5] approaches help both consumers and utilities. The demand shift from peak to off-peak hours will not necessitate the building of additional generating capacity. Construction of generating stations is expensive, leading in increased consumer rates. Load management participants pay varying fees during peak and off-peak hours, or are offered incentives to rearrange their loads. Peak load demand is reduced by integrating renewable energy resources such as solar panels, electricity output, and use during peak hours. To enable autonomous DSM in the future smart grid, various load management technologies have been investigated in the past. Incentives-based energy consumption controlling strategies were described in [6], [7] and [8], which explained a Direct Load Control (DLC) method for residential load control to enable demand side management. [9] describes a technique for scheduling residential energy consumption that employs Energy Management Controllers (EMCs) to schedule appliances [10], for example, have proposed a scheduling method based on priority in which according to the load curve, the appliance with the highest priority is turned on first and without restriction. Low priority devices are turned on with a slight lag. [11] discusses various household energy management techniques on the household energy management techniques on the future smart grid. The research has focussed DSM approaches in terms of load control techniques. DSM techniques can be divided into two types: time-based and incentive-based [12]. Power consumption during peak hours is monitored via time-based DSM techniques. The most typical DSM programmes for peak load management are load shifting, peak clipping, and valley filling [13].Although DSM is an important technique for reducing peak demand, developing countries have given far less thought to designing a suitable DSM strategy since DSM deployment poses some obstacles and barriers. A lack of smart metering, communications infrastructure, control techniques, information technologies, understanding the benefits of the DSM, competitiveness issues in comparison to traditional approaches, an increase in the complication of the system's operation, and inadequate market incentives are among the capital costs and lead times for implementation. In this paper peak load management using peak clipping, load shifting DSM techniques and integration of solar power in managing loads during peak hours is presented.

The remaining sections of this work are organised as follows. Section II discusses research problem and identified gaps. In section III, electrical load management of residential sector of India is presented. In section IV, the proposed methodology for peak power management of a residential building using different DSM strategies is discussed. Section V discusses the results of the proposed DSM Model for peak power control. Section VI presents the performance analysis of the proposed strategies in terms of PAR, peak power demand and billing cost of the consumers. We draw conclusions and propose recommendations for further research in section VII.

Research Problems and Gaps

Peak-to-Average Ratio (PAR) and peak load demand are reduced while energy consumption costs are reduced with optimal energy consumption scheduling. Using optimization algorithms, differential tariff based load scheduling, and incentive based load scheduling algorithms, numerous demand-side management strategies such as peak clipping, load shifting, and valley filling have been proposed in the literature in order to manage peak power demand. A peak load management (PLM) controller is required for energy consumption scheduling of household appliances to achieve the lowest energy consumption and reduce the peak demand allowing large number of consumers to take advantage of power limits, help utilities match the consumption and generation, reduce the component load, and improve grid efficiency and resilence.

The following research gaps have been found based on existing techniques for peak power management:

- Appliance scheduling is based on variable tariff for on peak and off peak hours using optimisation algorithms..
- There is no research being done to address the issue of peak demand management in developing countries where the power system is underdeveloped and no smart metres have been installed to record large amounts of historical data.
- No controller has been designed that automatically manages the loads during peak hours without causing a significant discomfort to the user.

As a result, there is a need to design a novel automated peak power management model that allows users to effectively participate in reducing power consumption during peak hours.

Residential Load Management

Since 1971, India's domestic energy consumption has surged by a factor of more than 50. India's electrified households account for less than a third of global power use. Rapid electrification, greater prosperity, and technical improvements may all contribute to a rise in appliance ownership and use. A better understanding of this demand can help with the development of effective energy-saving measures, the optimization of generation capacity increase, and the mitigation of climate change and pollution. However, until now, little attention has been paid to research on domestic electricity consumption in India. [14] In India, residential electricity consumption accounted for around 24% of total electricity consumption, second only to industry (about 42%), with agriculture (17%) and the commercial sector (about 9%) following closely behind (MOSPI, 2017). Between 2005–06 and 2015–16, the residential sector grew at a compound annual growth rate of 9%. The majority of electricity consumed in the home is for heating and non-heating purposes. Cooking, water heating, and ironing are examples of heating applications, whereas lighting, refrigeration, water lifting, and air circulation are examples of non-heating applications. Heating and non-heating uses account for 28.60 percent and 71.40 percent, respectively, of total electricity consumption.Fig.1 depicts the end use analysis of residential sector.

Load management typically attempts to achieve two goals in home settings: decreasing energy use and changing energy use. The use of more energy-efficient technologies, the construction of more energy-efficient structures, and the promotion of energy-conscious consumer practises all contribute to the first goal. The second purpose is achieved by shifting the operation of devices like washing machines and PHEV chargers from peak to off-peak hours, when energy prices are at their lowest. The PAR reduction is used to evaluate the DSM Controller's peak power clipping capability.

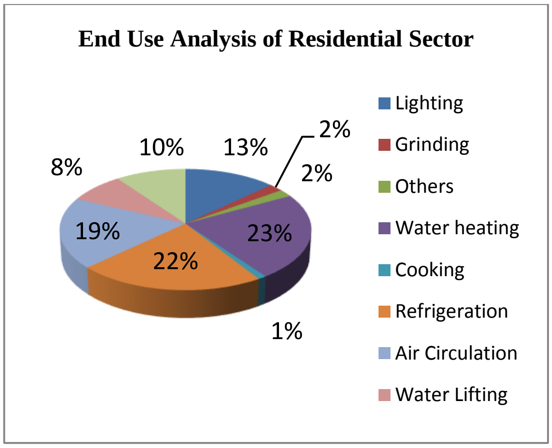

Fig.1. End use analysis of residential sector

Proposed Methodology

A novel peak load management (PLM) controller is created and simulated for energy consumption scheduling of household appliances in order to achieve the lowest energy consumption and reduce peak demand. The peak load management model is based on an apartment consisting of 11 houses with distinct areas and appliances. The peak load of the entire apartment is handled in the proposed work by scheduling the appliances of separate dwellings depending on load priority. To clip the peak power, a cascaded multilayer neural network, as shown in Fig.2, is utilised to generate control signals for various appliances in all houses of the building. Three control strategies have been proposed for peak load management. The first method is to apply peak clipping DSM, in which non-priority loads are turned off to lower peak demand according on consumer preferences. The second technique employs time-based scheduling, in which loads are turned on and off in order to shift demand from peak to off-peak hours, hence lowering peak demand. The third control approach, which is based on the availability of solar electricity, uses it to manage peak demand. Based on the connected loads, the amount of electricity consumed by each dwelling varies. In the study, seven types of loads were taken into account while modelling buildings; a few of these loads are common to all houses, while others are unique to each one.Table.1 shows the loads and ratings that were modelled for each dwelling.

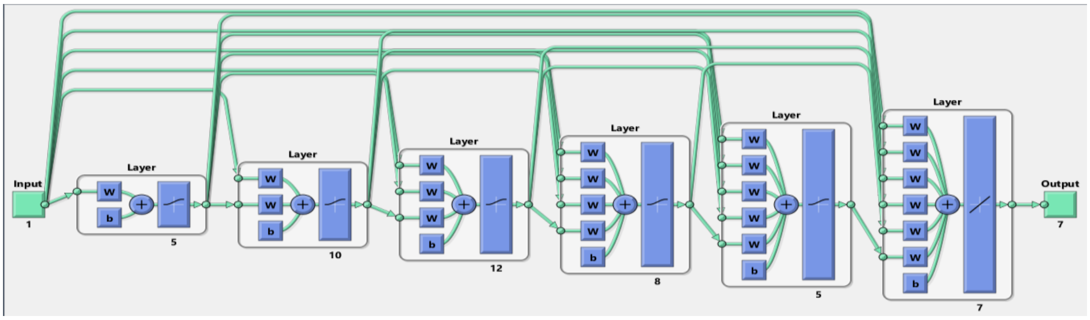

Fig.2. A Multilayer Cascaded Feed Forward Neural Network For Peak Power Clipping

Table .1 Modelled Loads with Rated Capacity

Load category	Rated Capacity in Watts										
	H1 4k	H2 5k	H3 8k	H4 9k	H5 4k	H6 5k	H7 8k	H8 9k	H9 4k	H10 5k	H11 15k
Lighting	200	250	600	500	200	250	600	500	200	250	1000
Entertainment	150	200	250	300	150	200	250	300	150	200	500
Kitchen Appliances	1500	2000	3000	3500	1500	2000	3000	3500	1500	2000	4000
Ac1	1000	1500	1000	1500	1000	1500	1000	1500	1000	1500	2000
Ac2	-	-	1500	1500	-	-	1500	1500	-	-	2000
Ac3	-	-	-	-	-	-	-	-	-	-	2000

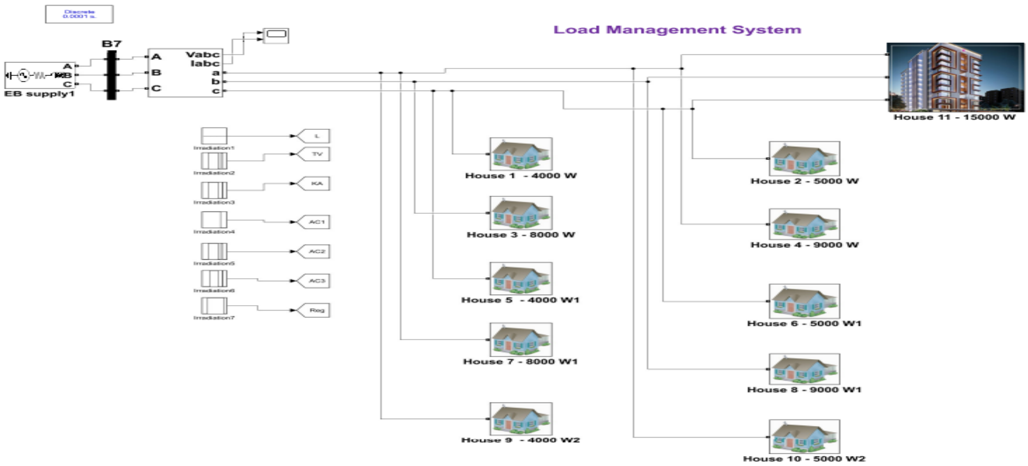

Fig.3. Simulink model of an apartment building

In the study, seven types of loads were taken into account while modelling buildings; a few of these loads are common to all houses, while others are unique to each one.Table.1 shows the loads and ratings that were modelled for each dwelling. Figure.3 depicts a Simulink model with 11 dwellings without controller. The control signals of the loads are used to generate the load curve of each individual house and the overall apartment structure. House 11 has a connected load capacity of 15000W and comprises of all seven loads as depicted in Table.1.

Peak load management using peak clipping

In the suggested model, a maximum amount of power that the building can consume during the day is set as a threshold. A 13kW threshold has been established in this circumstance. When this peak is exceeded, the controller is programmed to send out control signals that regulate the building's individual loads. To lower the peak power usage of the building, the loads that can be delayed are turned off based on the consumer preferences. Table.2 shows how the loads are shut off in order to lessen peak demand, which can happen at any time of day.

Table.2. Load preferences to reduce the peak demand

Appliance	Consumer Preference For Turn Off/Shifting
Ac3	1
Ac2	2
Ac1	3
Kitchen Appliances	4
Entertainment	5

As illustrated in Figure.2, the controller is built using multilayer cascaded feed forward neural. The suggested system uses a CFNN structure with seven hidden layers, which reduces the mean squared error to less than 10-4. The model was trained using two sets of data: one for power usage and the other for control signals for seven devices. Table.3 shows the details of the CFNN design.

Table.3.CFNN Architecture

Input Node	1
Hidden layers	6
Output Nodes	7
Interconnection	Cascaded
Activation Function	Sigmoid Function $S(t) = \frac{1}{1 + e^{-t}}$
Learning algorithm	Levenberg Marquardt

The training data is divided using the dividerand function, which divides the data at random with an 80 %, 10%, and 10% training, testing, and validation ratio, respectively. The six hidden layers employ a log sigmoid activation function, whereas the output node uses a linear activation function. To train multilayer CFNN architecture, the Levenberg-Marquardt algorithm is employed. The apartment complex's Simulink model with controller is shown in Figure 4.

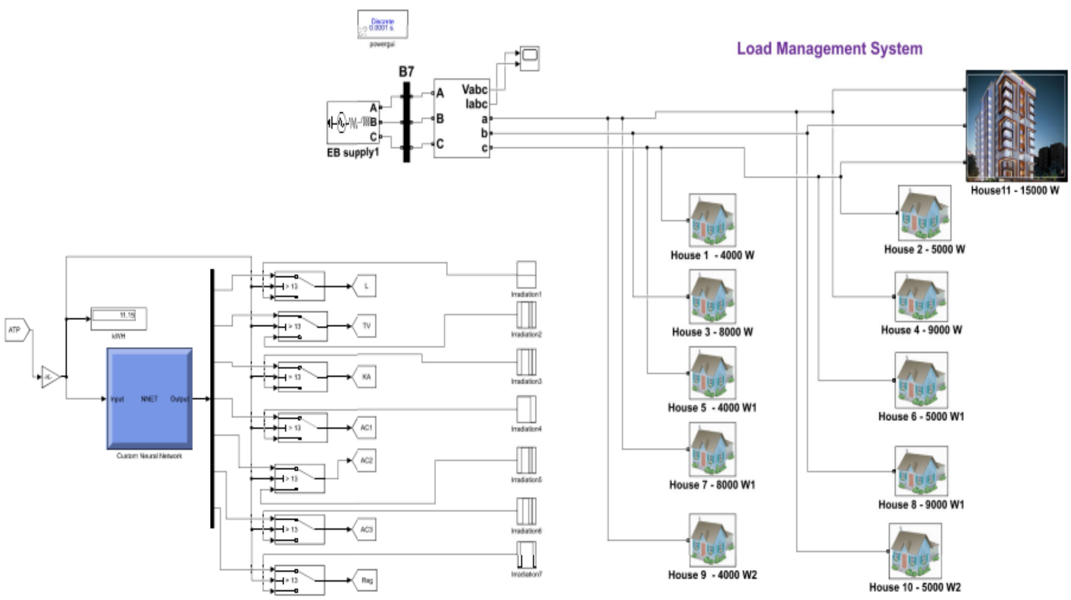

Fig.4. Simulink Model with Controller

The overall power consumption of the building acts as an input to the controller and once the peak power consumption reaches 13kW, the controller generates control signals to turn off the devices based on the preferences of the consumers, as shown in Table.2.

Peak load management using load shifting

The suggested approach achieves peak power management by controlling the on and off of devices in such a way that power consumption shifts from peak to off peak hours. Although average energy usage remains unchanged, peak demand is eliminated. To create the control signals, the same multilayer cascaded feed forward neural network is employed, with the same CFNN architecture as in Table.3. The training is oriented on time rather than power. The peak to average ratio is considerably reduced, resulting in lower billing costs.

Green energy (solar power) Integration into the grid for Peak Load Management

The electric grid supports small-scale generating within consumer premises, whether industrial or residential, with financial incentives. The deployment of distributed generators has helped both providers and customers while also improving grid resilience. In order to improve the effectiveness of such a decentralized network, traditional power systems have been moving from centralized supply side management to decentralized supply and demand side management. As a result, load management in the new operating environment is more complicated than in the previous one [15]. Owing to consumers ignorance most buildings' electrical energy use is currently inefficient. Grid overloading has become more common, especially during peak hours, and could lead to grid failure. In addition, a large amount of resources is squandered as a result of this. Through the use of techniques like Demand Response (DR), attention from the load end could result in a considerable improvement in this area. If consumption is monitored from the consumer's perspective rather than the supplier's, energy waste can be reduced more effectively.

Peak load management is handled by solar power generated in consumer's premises in the proposed system. When peak demand occurs, the DSM controller checks for solar power the loads are sourced from solar power if the solar power generated during the peak period is sufficient to fulfill the peak demand, lowering grid stress in order to meet peak power demand. The DMS controller takes over peak power management when solar power is absent or not sufficient enough to meet the demand. To simulate solar power generation, a solar power module with 7 series connected modules and 88 parallel strings of Matlab is utilised. The Simulink model with solar power integrated to the grid is as shown in Figure.5.

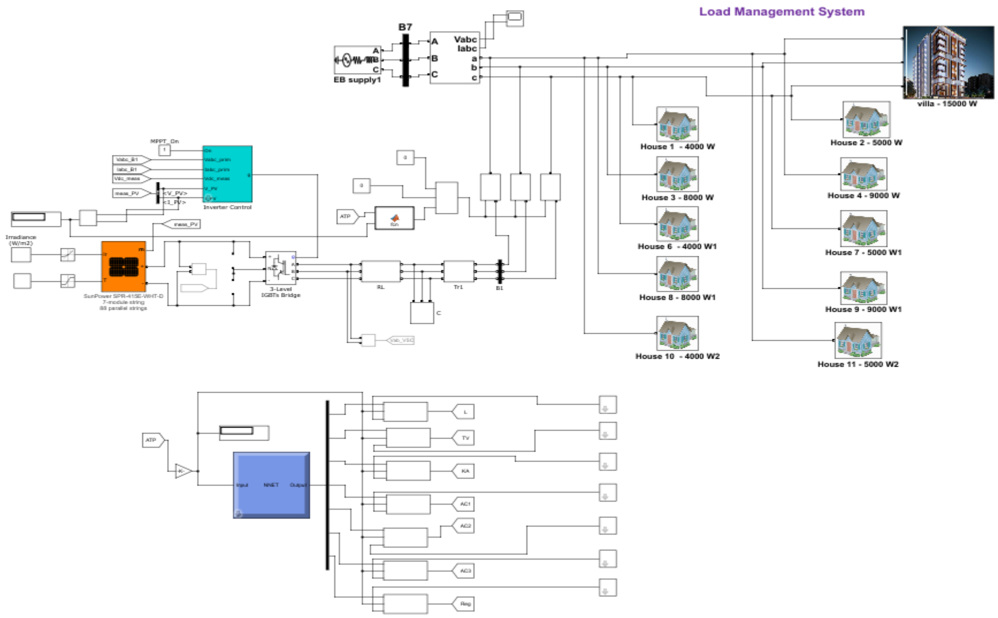

Fig.5.Solar Power Integrated Model

Results and Discussions

The performance graphs of a Multilayer Cascaded Feed Forward Neural Network training model for producing control signals for diverse loads based on peak power consumption and a Multilayer Feed Forward Network training model for generating control signals based on time are described in this part. Mean Square Error metrics, PAR, and billing cost are used to evaluate performance. The proposed cascaded feed forward neural network is tested and evaluated for peak clipping and load shifting, and the results are compared to other existing approaches. The results reveal that the proposed cascaded feed forward neural network outperforms the other methods.

The load curve of the building without a controller for a day is as shown in Figure 6 and the figure shows two peaks during the day, one occurs from 3 am to 5am and other peak from 2pm to 5pm. The peak power limitation is 13kW, the peak power for the above load curve is 13880.85W which occurs from 3 to 6 pm and at 5am.Hence the peak to average ratio for the apartment building without controller is given by

$$PAR = \text{Peak Power}/\text{Average Power} \text{----------} (1)$$
$$= 13880.85/9986.31=1.389$$

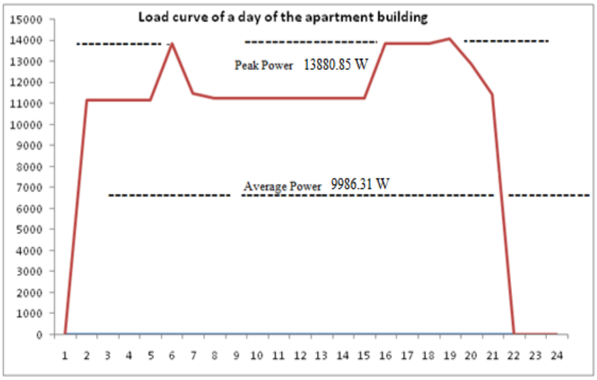

Fig.6.Load Curve of the Building without a Controller

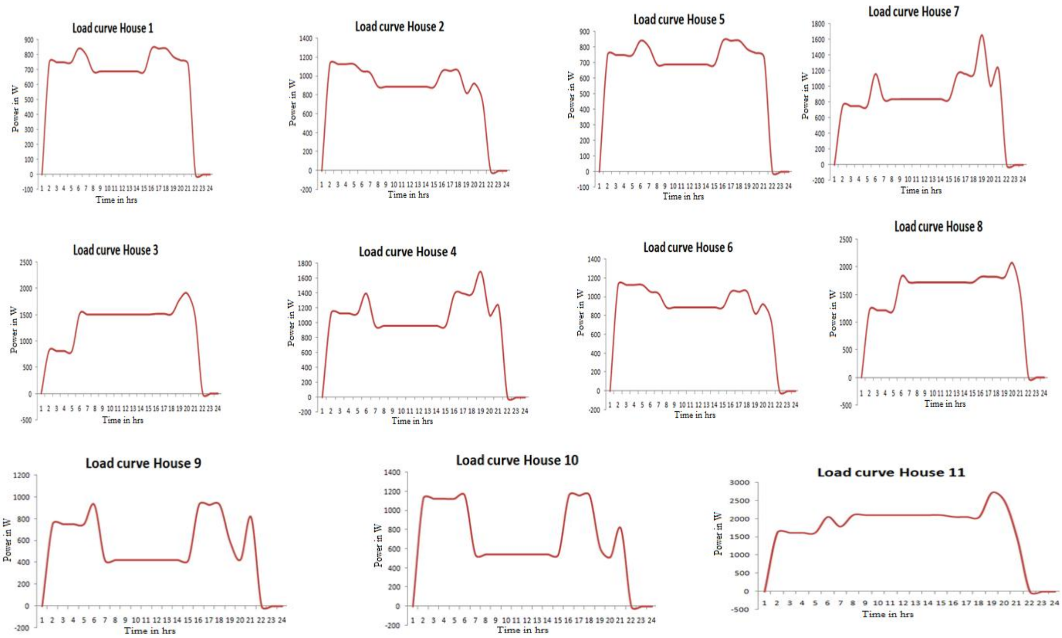

Fig.7.Load Curve of Individual Houses

The load curve of individual houses is as shown in Figure. 7. The daily billing cost of individual houses and apartment buildings is calculated using Karnataka Electricity Board's tariff structure, and is as shown in Figure.8 without the controller. The entire bill for a day in the unit is 12.78$. Similarly, load curves for each day can be shown, and monthly consumption and bill estimates can be calculated. If the load patterns are same for 30 days, the monthly charge without the controller will be

Monthly bill=Bill/day *30=30*12.78$= 383.4$

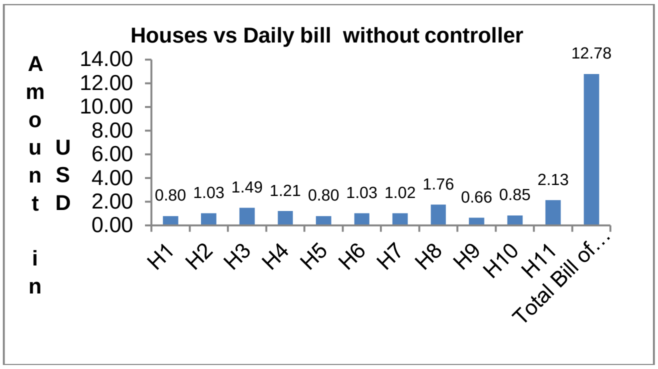

FIG.8 Houses Vs Daily Bill

Peak Load Management Using Peak Clipping Dsm Approach

With 3500 data, a multilayer cascaded Feed forward Neural Network model was trained on power consumption of an apartment for a day and load behaviour depending on power consumption. Validation checks, gradient error, and Mean Square Error can all be used to assess the training model's performance (MSE). Figure.9 depicts the validation performance curve. Epoch 145 had the best validation performance over the validation period, with an MSE of 9.375*10-6. The gradient error and validation checks are shown in Figure.10 for each epoch. At epoch 151, the gradient error is 0.023644, and there are 6 validation tests. A scatter plot of experimental data for training, validation, and testing is shown in Figure.11. The values of R for the training, validation, and testing periods are 0.99977, 0.99998, and 0.99782, respectively, as shown in this graph.

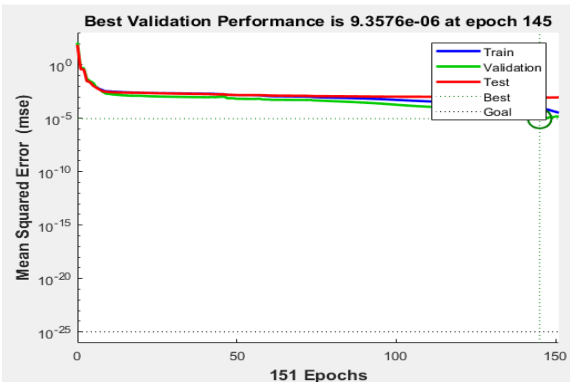

Fig.9. Validation Plot for peak clipping

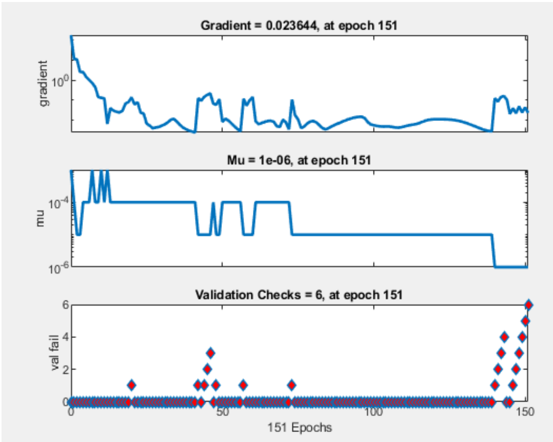

Fig.10. variation of gradient error and validation checks

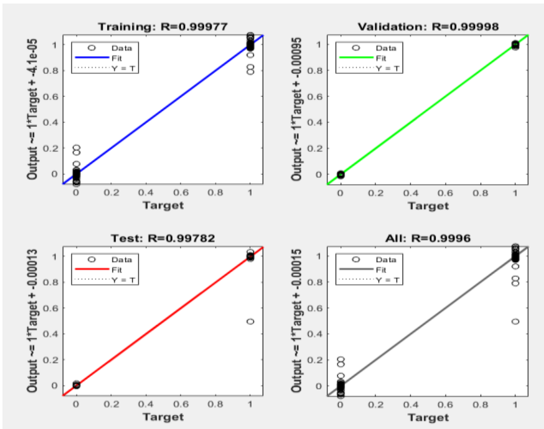

Fig.11.Scatter Plot For Training, Validation, Testing And All Data

The trained model creates signals that limit the peak power of the loads when they are turned on and off. Figure.12 shows the load curve with controller, and it can be seen that peak power is reduced owing to load switching off based on consumer preferences.

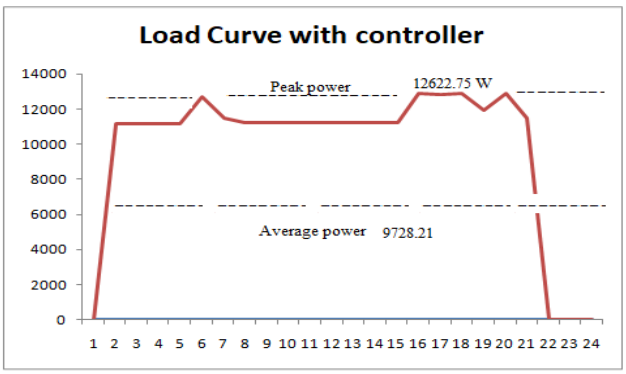

Fig.12 Load Curve Of The Apartment Building With Controller

The peak power limitation is 13KW, however the peak power has been limited with the usage of the controller, and the peak power with the controller is 12622.75W, which occurs between 3 and 6 p.m. and at 5 a.m. As a result, the peak to average ratio for an apartment complex with a controller equals

PAR=12622.75 W / 9728.21W=1.2975

The billing cost of individual houses and the apartment building for a day is computed with controller as shown in Figure.13.

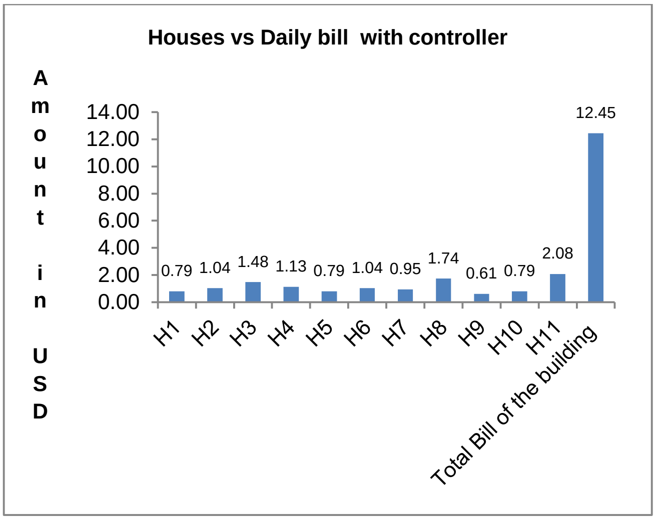

Fig.13. Houses Vs Daily Bill With Controller

For a day, the cumulative bill of the apartment is 12.45$.Similarly the load curves for all the days can be plotted and the monthly consumption as well as the monthly bill can be estimated. Assuming similar load patterns exist for 30 days,then the monthly bill with controller will be

Monthly bill=Bill/day *30=30*12.45$ = 373.5$

Peak Load Management Using Load Shifting Dsm Approach

With 148 samples a multilayer cascaded Feed forward Neural Network model was trained on the switching behaviour of loads based on electricity consumption over the day. Validation checks, gradient error, and Mean Square Error can all be used to assess the training model's performance (MSE). Figure.14 depicts the validation performance curve. With an MSE of 0.08058, Epoch 14 had the best validation performance over the validation period. Figure.15 depicts the gradient error and validation checks for each time. The gradient error at epoch 14 is 0.017007, and there are 6 validation tests. Figure.16 depicts a scatter plot of experimental data for training, validation, and testing. The values of R during the training, validation, and testing periods are 0.9454, 0.83972, and 0.9454, respectively, as shown in this graph.

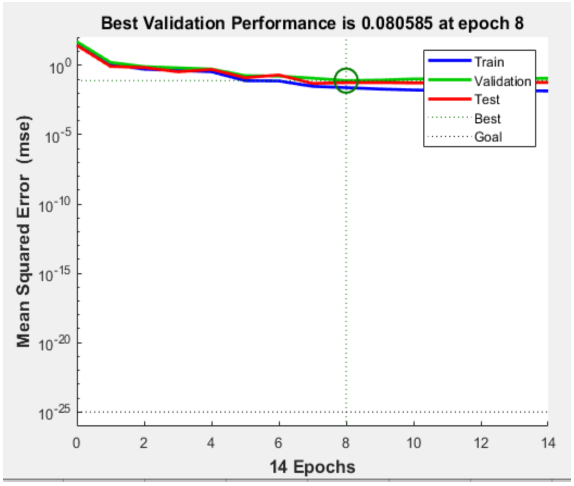

FIG.14. Validation Plot for Load Shifting Model

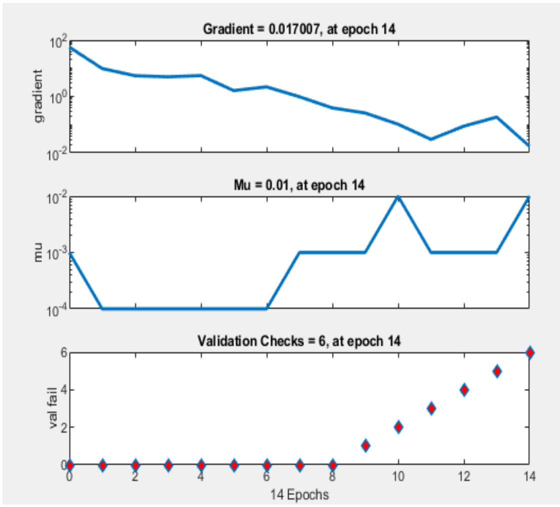

FIG.15. Variation of Gradient Error And Validation Checks

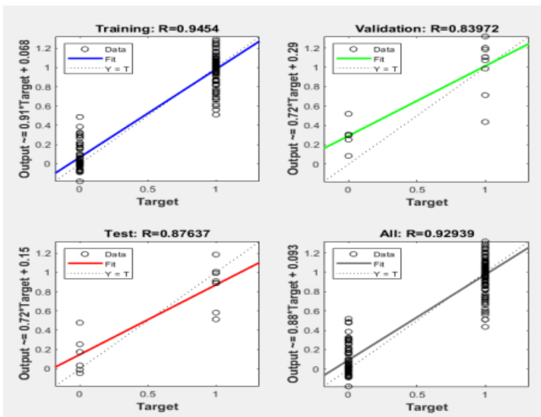

FIG.16. Scatter Plot For Training, Validation, Testing And All Data

The model is trained to generate control signals that automatically control the appliance switching in such a way that the peak power is limited by shifting the loads from on peak hours to off peak hours. The load curve with controller is shown in Figure 17, from the figure one can observe the reduction of power between 3 and 6 pm which was achieved due to controlling the switching of loads based on the priority assigned by the consumers. The peak now occurs at a different time interval, from the graph the peak is allowed between 3 am to 5 am. The peak to average ratio for the apartment building with controller is given by

PAR = 13.57 KW/ 11.02KW= 1.2313

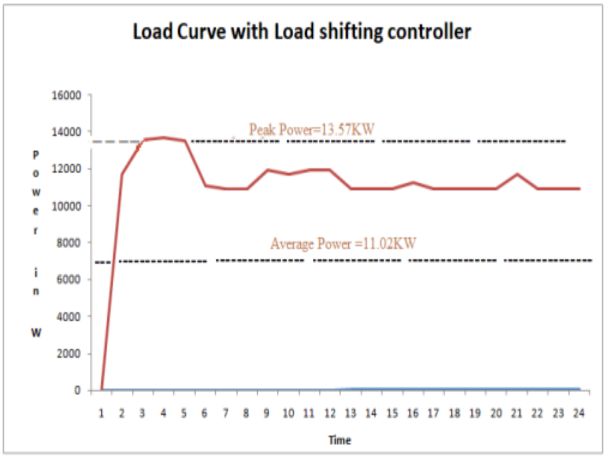

FIG.17. LOAD CURVE WITH PEAK SHIFTING CONTROLLER

The billing cost of individual houses and the apartment building for a day is computed with load shifting controller as in Figure.18.

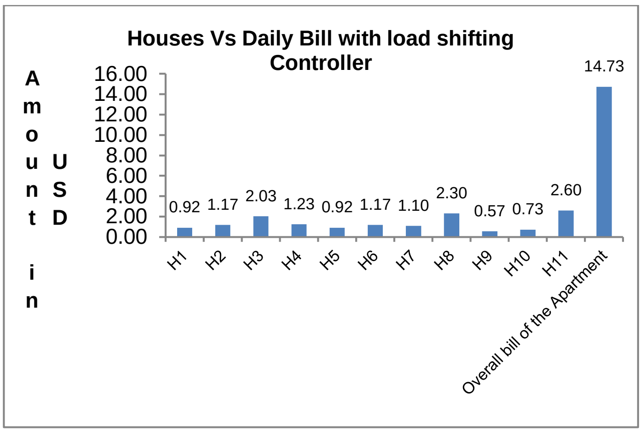

FIG.18.Houses Vs Daily Bill With Load Shifting Controller

Since the GOK tariff system is flat rate and not variable, the house bill with load shifting controller is 14.73$ which is greater than the bill without controller. The users can be awarded with an overall rebate or rebate on their monthly bill for modifying their usage of appliances during peak hours and shifting them to off peak hours reducing the burden on the grid.Consumers in this sort of DSM have the freedom to use their full loads during off-peak hours with no peak limit.

Peak load management using solar power integrated to the grid with controller

The same CFNN controller used for peak clipping is employed in conjunction with a grid-connected solar power source for peak load management. The loads are linked or detached from the grid depending on the availability of solar electricity to meet the peak demand, which is set at 13kW. The solar controller checks for the availability of solar electricity that would meet the building's peak demand when the peak exceeds the authorized peak power demand. If the solar power generated is larger than 13k, the loads are connected to the solar power source instead of grid which allows the consumers to continue their usage of appliances even during peak hours. If the solar power is insufficient to meet the peak limitation during peak hours, the MLCFNN controller regulates the peak by shifting off the devices according to the preferences. The load curve with grid integrated solar power is as shown in Figure.19

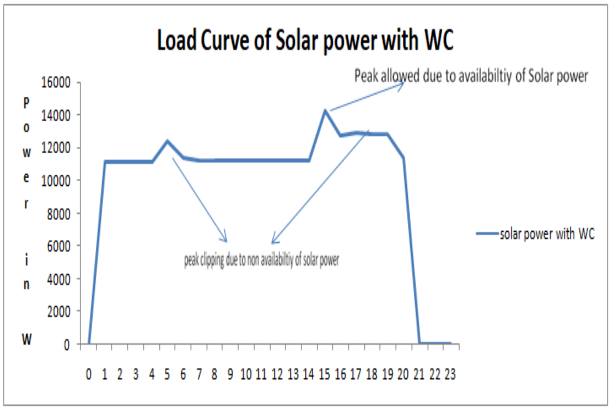

FIG.19. Load Curve of Building with Solar Power Integrated With Controller

The maximum power output is limited to 13 kW, and the maximum power output is governed by the solar integrated controller. For an apartment building with a solar power controller, the peak to average ratio is

$$PAR = 13880\ W/10217.78\ W = 1.3584$$

Performance Evaluation

The PAR reduction and bill cost are used to evaluate the DSM Controller's peak power clipping performance.Figure.20 represents the load curves of the power consumed in the apartment during the day with and without the controller. The controller is successful in limiting peak power and thereby lowering PAR and billing costs. The plot of daily house bill with and without controller is shown in Figure.21. With the help of the DMS controller, a significant reduction in bill is obtained for each house and the entire apartment complex.Figure.22 represents the overall load of the apartment complex and the curve with controller represents the shifting of the peak power from peak hours to off peak hours. During the peak period, peak demand decreased from 13.88kW to 11.25KW. The controller with load shifting allows the user to employ full loads at any other hours other than peak hours.

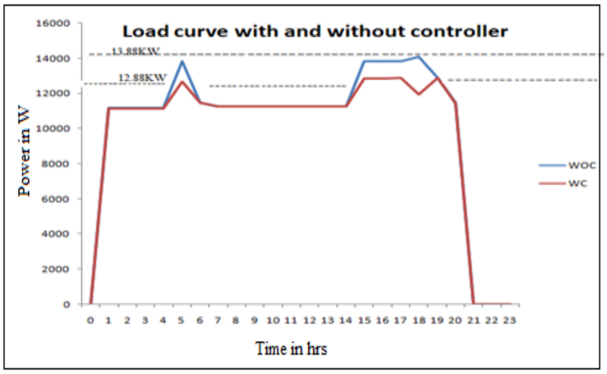

FIG.20. Load Curve With And Without Controller With Peak Clipping

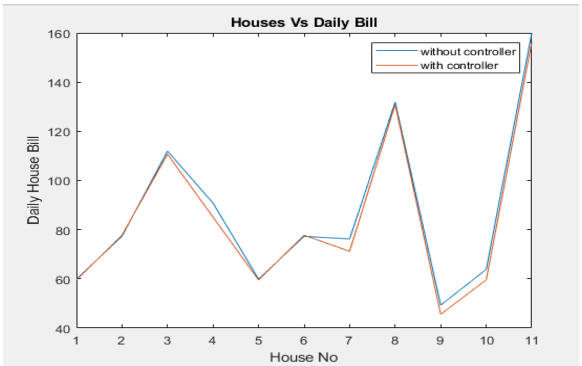

FIG.21. Houses vs Daily Bill with and without controller

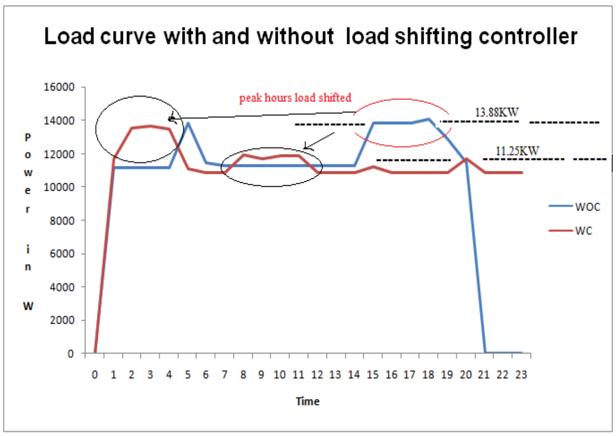

FIG.22.Load Curve With And Without Load Shifting Controller

The PAR reduction is used to measure the performance of the DSM Controller for peak power clipping with solar integrated into the grid. Figure.23. represents the load curve of apartment building with solar power integrated to manage the peak load with and without controller.

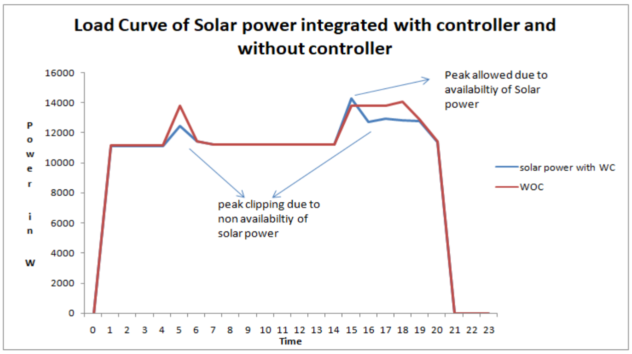

FIG.23. Load Curve of solar power integrated with controller and without controller

The consumers are disconnected from the grid and connected to the solar power source based on the availability of solar power during peak demand; the consumers have the flexibility to operate their full loads during peak demand without putting a burden on the utility due to the use of an alternate power source. The performance of the DSM techniques during peak hours is seen in Tables 4 and 5. During the peak period of 3pm to 6pm, a peak power reduction of 5KW and 11.6KW is achieved.

Table.4. Reduction In Peak Power Using Peak Clipping DSM

Time (Hours)		Load (kW)		
From	To	Before DSM	After DSM	Difference
14	15	13.81	12.85	0.96
15	16	13.82	12.84	0.98
16	17	13.82	12.88	0.94
17	18	14.07	11.92	2.15
Total				5.03kW

Table.5.Reduction In Peak Power Using Load Shifting

Time (Hours)		Load (kW)		
From	To	Before DSM	After DSM	Difference
14	15	13.81	11.25	2.56
15	16	13.82	10.89	2.93
16	17	13.82	10.89	2.93
17	18	14.07	10.89	3.18
Total				11.6 kW

Peak clipping DSM reduced average peak power by around 1.25 kW, whereas load shifting DSM reduced average peak power by about 2.9 kW.

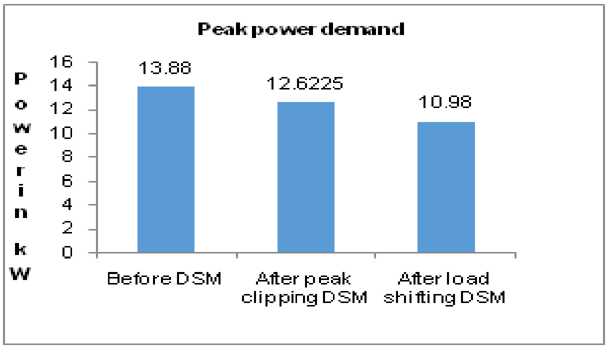

FIG.24. Average Peak Power Reduction

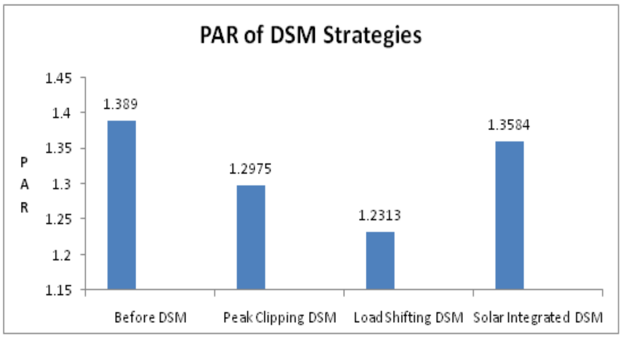

FIG.25. Peak To Average Ratio

Conclusion

In smart grids, peak power management is a key feature of DSM. A multi layer cascaded feed forward neural network is used to implement a controller for managing peak demand using three different strategies. Using Matlab and Simulink, the suggested model was simulated and tested for an apartment building with 11 houses and varied loads. The simulation results and performance analyses are tabulated with explanations in the findings and discussion. According to the findings, the proposed technique reduces peak power by 5.03kW, 11.6kW, and PAR by 1.2975, 1.2313, and 1.385 for DSM techniques that are implemented. To achieve the desired goal, the proposed model was effectively developed and evaluated.

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