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Demand Side Management: An Alternative to Load Shedding in Tanzania's Grid Distribution System.

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Abstract : ***Electrification is the fastest-growing and widely adopted trend across all industries and geographical areas in Tanzania. This rapid expansion has led to an increased demand for electricity. Similarly, dependence on hydropower makes it vulnerable to droughts, results in energy deficits, and cannot meet rising electricity demand. To address this growing demand, the Tanzania Electricity Supply Company (TANESCO) have resorted to load shedding, but it has proven inconvenient for customers. Alternatively, constructing new power plants cannot immediately meet the rising demand. This study aims to explore demand-side management as a viable alternative to load shedding, and reducing the necessity for new power plants. The study employs artificial neural network optimization method to optimize the battery energy storage system to lower the peak demand through peak clipping. The proposed study was modelled and simulations were carried out using the MATLAB/Simulink R2022a software environment. The results show that the proposed approach effectively reduces peak demand, and consequently achieving significant reductions in the peak-to-average ratio (PAR), leading to improved grid reliability and efficiency. Notably, the study demonstrates peak demand and PAR reductions of approximately 41.8027% for grid-connected battery energy systems. Furthermore, this approach promises more flexibility and comfort for customers, making it a promising solution to address the challenges posed by increasing electricity demand and ensuring a reliable and efficient grid system.***

***Index Terms* - Artificial neural network, battery energy storage system, demand side management, load clipping, microgrid, peak demand.**

I. INTRODUCTION

Hydro power is the second major source of electricity in Tanzania as of 2020 Power System Master Plan (PSMP) but expected to dominate the electricity generation in 2024 after the completion of 2115 MW Julius Nyerere Hydro Power Plant[1]. The nation's 1,602.32 MW of installed capacity is made up of a connected Grid System (1,565.72 MW) and an isolated Grid System (36.60 MW). 573.70 MW (36.64%) of the interconnected grid system is hydro power while others are natural gas 892.72 MW (57.02%), liquid fuel, 88.80 MW (5.67%) and biomass 10.50 MW (0.67%)[2]. The difficulties Tanzania's electricity sector is facing include Tanzania's dependence on hydropower which makes it vulnerable to droughts and other weather-related events that can disrupt the supply of electricity. As a result, Tanzania has an energy deficit and cannot meet the growing demand for electricity. In the past two years the country has faced the drought[3] which led to the decrease of water level in several hydro power plant dams across the country leading to low generation of electricity.

Following the challenge, the utility has initiated load shedding in order to cater the challenges. Load shedding is when utilities step in on the supply side to minimize power use; customers are disconnected for a certain period of time[4],[5]. Customers typically hate this experience because it results in several losses and inconveniences[5]. Other alternative way to handle this challenge is to use large storage devices. A better alternative to load shedding is through demand side management where the peak demand is lowered through peak clipping

Demand side management (DSM) is defined as the planning, implementation, and monitoring of utility distribution network activities aimed at influencing customer electricity use in ways that result in desirable changes in load shape. The DSM system may dispatch available energy in a conservative manner, reducing emissions and peak load usage while allowing users to use their preferred energy type[6]. DSM was initially launched in 1970[7] in which the DSM model and architecture by the electricity industry was proposed to regulate the time of use (ToU) and the peak energy demand and the analysis of load profiles among consumers. DSM has gained more attention since it can reduce the peak-to-average ratio (PAR) by clipping the demand at the peak usage hours to make grid more efficient and reliable[8], improving load factor as a result of load shifting, maximization of electricity consumption from local renewable energy resources (RESs), minimization of cost of electricity, reduces inconveniences caused by load shedding and maximize user's comfortability, reduce the need for new power plants and improve the overall efficiency of the energy system[9], [10].

The various changes in the load patterns of customers demand can be shaped to improve utilization factors and load balance. The most frequently used load shape changes are through DSM techniques shown in Fig 1. Peak clipping tries to reduce peak demand in a utility system by lowering demand-side on-peak electricity consumption. This strategy is being implemented primarily to reduce current and future capacity needs. The most common method for achieving this change is to disable or restrict the operation of specific electricity-using equipment during peak hours by charging higher costs, directly managing loads, and incentivizing users[11] and the strategy is useful when there is no option of establishing or installing new power plants[10]. Valley filling aims to encourage increase of consumption during off-peak periods of very low electricity profile. Such actions are appropriate to perform when the incremental cost of serving the load is lower than the average cost of electricity. Increase of off-peak consumption lowers the average cost of electricity and it improves the utilization of available plants. Thence keep the demand and supply balance, avoiding the startup and ramp up cost of the generators[8],[11]. Load shifting gives the customers options to transfers loads usage patterns that would otherwise occur on- peak to off-peak periods based on cheap tariffs, thus combining peak clipping and valley filling. This is possible with distributed generation, energy storage systems and thermal storage technologies, such as the cool storage, heating storage and storage water heating[12]. Load growth is intended to enhance overall electricity sales. Customers are encouraged to raise their usage up to a specific level in order to keep the grid stable, e.g. using electric vehicles, heating and water heating systems[11], [12]. Flexible load shaping is a concept related to reliability in which customers are flexible enough to shift their loads to different low usage slots. The load shape can be flexible if the options presented to the customers include variations in quality of service in exchange for appropriate incentives. Interruptible or curtailable loads, or individual customer devices capable of incorporating service limits into load control actions, may be used in the programs[11]. Load conservation or Energy Efficiency entails reducing overall electricity consumption. This can be accomplished by the use of more efficient appliances, modifications to the building envelope, or other measures that reduce customers' electricity consumption[12], for instance, use of LED lights, BLDC fans, inverter ACs etc which are energy efficient appliances.

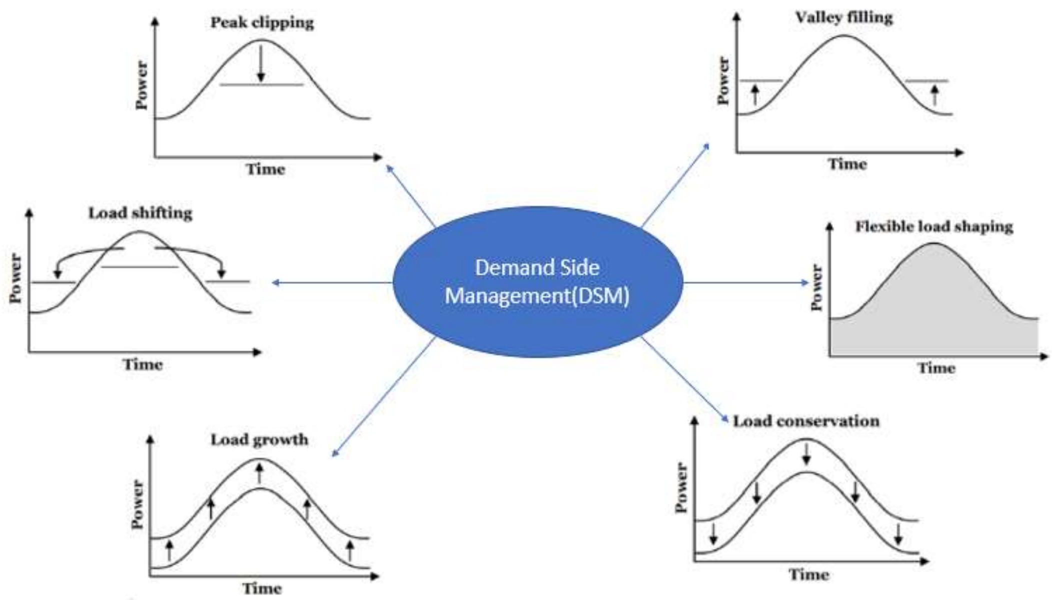


Fig. 1 Different demand-side management (DSM) techniques adapted from [9]

II. RELATED WORK

In recent years, DSM has received considerable attention from researchers, policymakers, and utilities for improving energy efficiency, reducing peak demand, and improving power grid reliability and stability: The authors of [10] provides an in-depth review on the demand side management techniques and optimization methods used residentially. Optimizing DSM strategies is crucial for minimizing energy consumption and meeting consumer demand. In [13], [14] the authors proposed a stochastics scheduling framework in which stochastic character of the electrical and thermal loads, renewable generation, and market prices are incorporated. Peak shaving DSM techniques was employed in [13] to minimize the total cost of energy, while [14] considered incentive based demand response (IBDR) and real time pricing (RTP) programs to maximize the profit of the microgrid operator while minimizing the energy purchase cost and improving reliability indices under normal and resilient conditions. Further, under uncertainty [15] proposed a two stage robust optimization model to minimize the overall electricity cost for customers and schedule of operating modes of different appliances. Nash Equilibrium(NE), a simple game theory was employed to study demand side management in [16] in which the loads were categorized into six groups based on their criticality and power requirements. A simulation of a specific day load with varying power availability shows the Nash Equilibrium based algorithm performs effectively and can help in managing the demand for electricity during peak hours and reduces the chances for blackouts. In [17], particle swarm optimization method was used to study demand side management in smart grid. It optimized the consumption curves of household, commercial and industrial consumers which minimize the cost incurred by the users while considering their preferences for loads by setting priorities and preferred time intervals for load scheduling. Demand side management for large-scale buildings with industrial loads was proposed and implemented using Genetic Algorithm(GA) to optimize the load curves and to generate an optimal schedule for industrial user based on controllable loads[18]. Backtracking search algorithm was used in [19] to solve two problems related to demand side management: reduction of load peak and minimization of the electricity bill for end-users. Clustering customers based on their load profiles and then applying the fuzzy logic-based DSM to each cluster to optimize energy consumption and reduce peak demand was proposed in [20]. [21] modelled a customized fuzzy logic control system to schedule household appliances and maintain consumer comfort levels for managing heating, ventilation and air conditioning systems in smart grid.

The authors in [22] discusses the use of demand side management(DSM) techniques in the context of smart grid, in which the authors used data acquired from digital meters to create load curves and train an artificial neural network (ANN) to classify new data based on created load patterns. In [9] a novel approach to demand-side management in microgrid systems through load shifting and peak clipping using neural network was presented. The proposed strategy increases the flexibility on the demand side by scheduling users' consumption patterns profiles in response to supply considering presence of deferrable loads. Through simulations, the study demonstrates that the proposed demand-side management (DSM) strategies can optimize the load profile with the solar generation, leading to better utilization of the available solar energy. Peak clipping reduced peak demand and PAR by approximately 31.2% and 7.5%, respectively. Meanwhile, load shifting offers more flexibility to customers, allowing them to reschedule their appliance usage to hours of more power generation. Further, in [23] neural networks was implemented as a control system for DSM in residential sector with distributed generation. The scheduler of the control system set the time to execute the task considering the user's constraints and generation forecast, while the coordinator of the control system manages the energy resources to meet the user's demand while maximizing the use of local generation. In [24] the application of demand side management to industrial customers using artificial neural networks was presented to improve the load factor and reduce the maximum demand, resulting in energy saving and cost reduction. Strategies like end-use equipment management, load prioritization, peak clipping and valley filling, and differential tariff were used to make best use of the energy sources that are currently available. To deal with uncertainty in future pricing, [25] employs a steady price prediction model based on artificial neural networks, while the best selections for various household appliances are made using multi-agent reinforcement learning. The algorithm handles energy management for multiple appliances, minimize user energy bills and dissatisfaction costs, and assists the user in significantly lowering its electricity cost compared to a benchmark without demand response**.**

Furthermore, various countries are implementing DSM to balance their power grid by matching the supply and demand, the US and UK are the leading developed countries implementing DSM, while India, South Africa and Nigeria are developing countries that have implemented DSM in their power system. Focusing on developing country like India; the Energy Conservation Act of 2001 in India aims to reduce energy intensity and has established the Bureau of Energy Efficiency to provide a regulatory framework. The Act includes schemes such as standard labeling of equipment and appliances, which enables consumers to choose energy-saving products. Another scheme is the Energy Conservation Building Code for commercial buildings, which aims to deliver cost-saving tools and is projected to save 125 billion units of electricity by 2030[26]. DSM in India is categorized into different aspects, including energy efficiency in the small and medium enterprise (SME) sector. [27] highlights the practical implications of implementing demand-side management (DSM) techniques in an Indian village, specifically Singhana Village (Dedali B) in Madhya Pradesh, India. Through the adoption of a demand-side management approach, the village can achieve a 15% reduction in energy consumption and a 20-25% decrease in electricity bills. The study employed the Binary Particle Swarm Optimization Algorithm to validate the effectiveness of the demand-side management approach and to optimize the scheduling of devices for efficient load management within a smart grid framework. The simulation results demonstrate notable reductions in peak load demand and total incurred costs, affirming the efficacy of the demand-side management approach. This study underscores the potential benefits of demand-side management in surmounting financial, social, and ecological constraints that often impede the construction of new power plants and the expansion of power transmission infrastructure. Though there is high awakening in implementing DSM in developing countries yet they are still facing challenges like lack of necessary infrastructure to support DSM programs, such as smart meters and advanced communication systems, low awareness and participation of consumers and at times policy and regulatory frameworks in developing countries may not be conducive to DSM implementation[28].

According to previous studies, DSM has not been effectively utilized and implemented in Tanzania, while many of these demand side management strategies are commonly adopted in developing nations. Moreover, the current electricity regulations in Tanzania do not promote the integration of microgrids and other renewable energy technologies into the grid, despite their potential to enhance grid stability. Conversely, the heavy reliance on hydropower renders the grid more vulnerable during drought seasons, resulting in reduced generation capacity and necessitating the utility to implement load shedding.

In this study, we employed the peak clipping DSM method within a model of a grid-connected battery energy storage system. Our aim was to showcase the significance of supply-demand matching of power during peak periods that is still lacking in Tanzania. This alignment not only enhances user comfort but also bolsters the reliability and efficiency of the grid system, particularly during periods of low generation from existing power plants. The key contributions of our work are outlined as follows:

- Implementation of a load clipping DSM approach on a grid-connected battery energy storage system.
- Utilization of an artificial neural network optimization method to regulate the output of the battery energy storage system (BESS).

The subsequent sections of the paper are structured as follows. Section 3 delves deeper into the technique, encompassing detailed explanations of the model construction and simulation process. In Section 4, a comprehensive presentation of the paper's results and subsequent discussion is offered. Finally, Section 5 serves as the concluding segment.

III. MATERIAL AND METHODS

A. Load Data.

We can classify the loads based on where they are used, mostly classified as residential loads, commercial loads, and industrial loads. In this work we only take into consideration residential and commercial loads as they are usually supplied in common feeders while most of the industrial loads have separate feeders or private feeders. The load data used in this work are locally obtained load data in a span of 30min for one day and are used to show how demand side management can be implemented in a grid connected battery energy storage system with neural network as an alternative to load shedding in Tanzania grid distribution system.

Table 1 Load Data

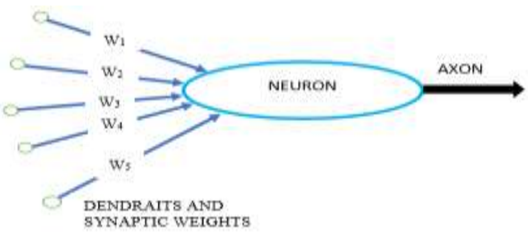
ToD (hr)	Residential Load		Commercial Load	
	P (in watts) for R-1	P (in watts) for R-2	P (in watts) for C-1	P (in watts) for C-2
0	4240	8400	12000	2500
0.5	4240	8200	11000	2375
1	4200	8000	10000	2250
1.5	4200	7950	9000	2125
2	4200	13200	8000	2000
2.5	4000	12750	7500	2075
3	4000	12900	7000	2150
3.5	4000	9300	6750	2275
4	3800	10400	6500	2400
4.5	4335	10450	6250	2575
5	4615	10500	6000	2750
5.5	4600	10600	7000	2625
6	4580	10760	8000	4500
6.5	4530	10810	9000	7150
7	4480	10860	10000	9800
7.5	4480	12335	10000	18400
8	4480	13710	10000	27000
8.5	4750	14235	14000	31500
9	5000	14760	18000	36000
9.5	5100	15180	21500	47500
10	5180	15600	25000	59000
10.5	5290	16600	30000	56000
11	5400	17600	35000	53000
11.5	5390	20280	35500	67750
12	5380	24960	36000	82500
12.5	5370	24810	36500	90250
13	5360	24660	37000	98000
13.5	5000	22280	38500	92750
14	4640	19900	40000	87500
14.5	4650	16700	40000	80250
15	4660	13500	40000	73000
15.5	4600	14700	39500	67000
16	4600	15900	39000	61000
16.5	4600	16125	38500	53750
17	4600	16350	38000	46500
17.5	6200	15700	37250	40750
18	7800	15050	36500	35000
18.5	7800	14775	29250	29750
19	7800	14500	22000	24500
19.5	7800	14300	21000	20000
20	7800	14100	20000	15500
20.5	6700	14150	19750	11000
21	5600	14200	19500	6500
21.5	5600	14250	18750	5750
22	5600	14300	18000	5000
22.5	5000	13450	16500	4000
23	4400	12600	15000	3000
23.5	4320	10500	13500	2750

B. Battery Energy Storage System.

BESS is a device that enables energy to be stored and then released when needed. They offer several benefits over traditional grid storage solutions, including balancing the electric grid, providing backup power, improving grid stability and enabling the use of renewable energy. Furthermore, the current technology of choice of BESS is lithium-ion batteries due to their cost-effectiveness and high efficiency[29]. The average duration of utility-scale lithium-ion battery storage systems is 1.7 hours but it can reach 4 hours[30], while the long duration batteries, can discharge for about 10 hours. The degree of autonomy can also affect the operation hour of a grid-connected battery, as it depends on the size of the battery, the amount of energy being consumed, and the rate at which it is being recharged[31]. In this study the BESS of 100kW was used, with initial state of charge of 50%. The BESS connection to the grid is as seen in the simulation figure marked as fig 2. On the other hand, fig 3. Shows the measurements from the system, including the battery's state of charge (SOC).

C. Artificial Neural Network

Artificial Neural Networks are a type of machine learning that mimic how biological creatures learn. It is inspired by the structure and function of brain whereas the nervous system comprises neurons, which are linked to each other through axons and dendrites and their junction is known as synapses which modify the response to stimuli, and this modification is how the living organisms learn[32], [33], [34]. Thus a processing unit called neurons performs computation in artificial neural network connected to one another through weights, which serve the same role as synaptic connections in biological organisms[32]. This architecture is illustrated in figure 4a and its modification in figure 4b.



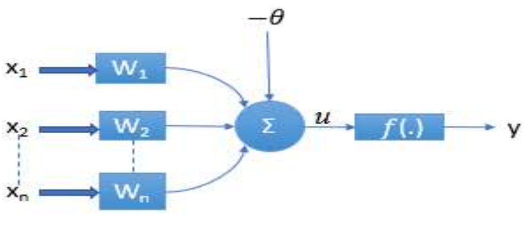


Fig 4 (a) Artificial Neural Network; (b) Modified Artificial Neural Network

The output of artificial neural network can be drawn from the above modified architecture;

$$y = f(u) = f\left(\sum_{j=1}^{n} w_j x_j - \theta\right) \quad (1)$$

Where: y: Output Signal
f: Activation function
u: Activation potential
θ: Activation threshold
$W_1, W_2, \ldots, W_n$: Synaptic Weights
$X_1, X_2, \ldots, X_n$: Input Signals

The basic architecture of Artificial Neural Network consists of three layers which are, Input layers - in charge of receiving information (data), signals, characteristics, or measurements from the outside world; Hidden layers - made up of neurons that are in charge of extracting patterns linked with the process or system being studied and Output layers - in charge of producing and displaying the final network outputs that arise from the processing conducted by the neurons in the previous layers

The flowchart in fig 5 below is used to implement the artificial neural network in this proposed model. The flowchart also includes the five stages such as data acquisition, creating patterns, choose ANN, training and simulation and validation taken to reach the required trained model.

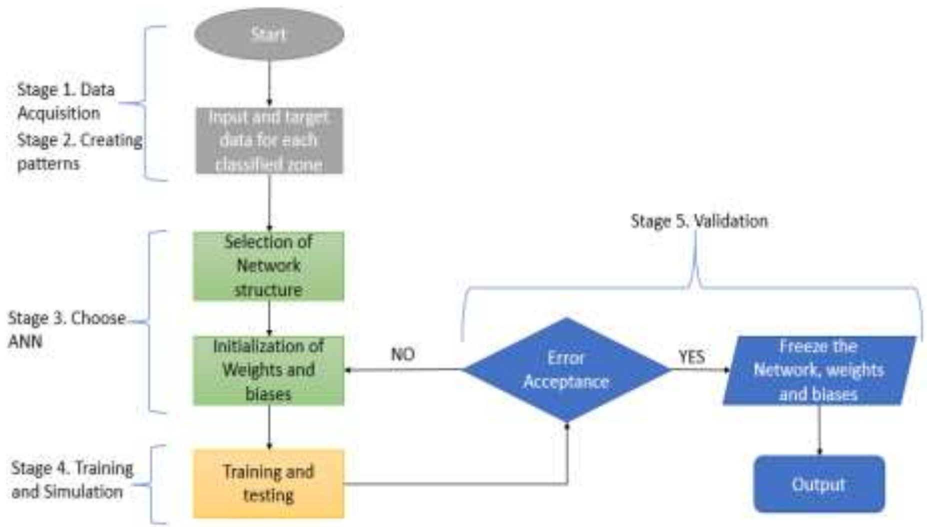


Fig 5 Flowchart for Artificial Neural Network implementation

D. Training of Artificial Neural Network

MATLAB ANN toolbox software is used for this simulation with three layers of feedforward architecture namely input, hidden and output layers consisting of 2, 30, and 1 neuron. For most typical problems, a rough prerequisite for the number of hidden layer neurons is the rule of geometric pyramid. Means as the number of layers increase, the performance increases but when a certain threshold is reached as the number of layers increase, the performance decreases -see figure 6.

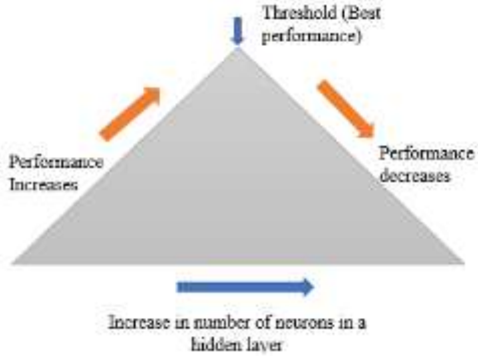


Fig 6 Network performance with increase of number of neurons in a hidden layer.

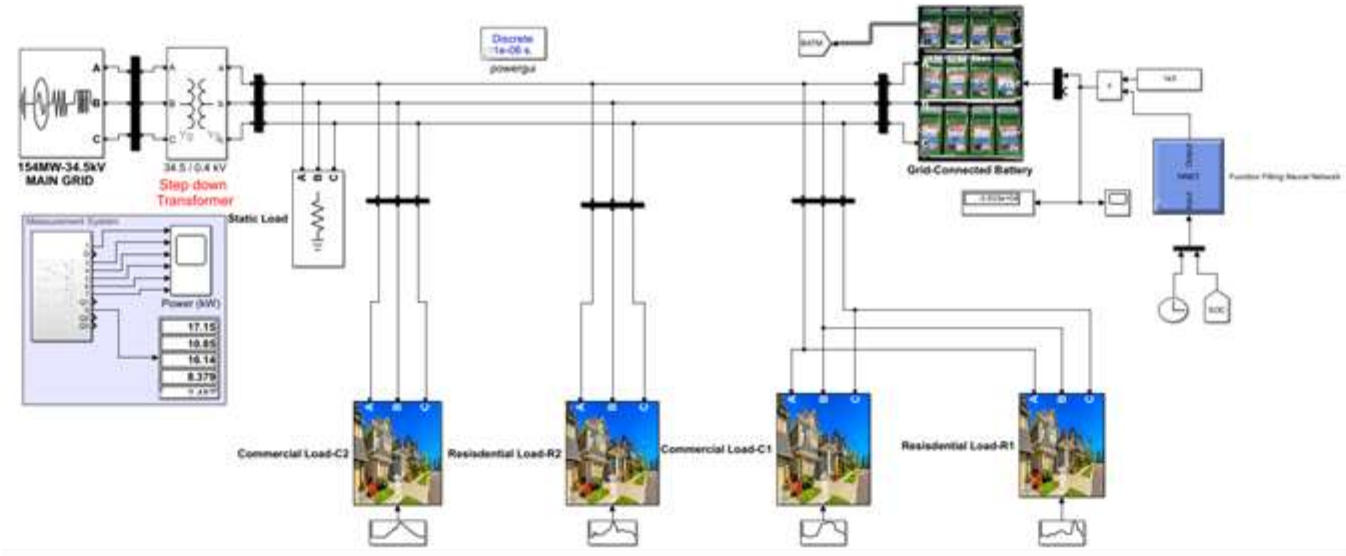


Fig 2 Grid connected battery energy storage system.

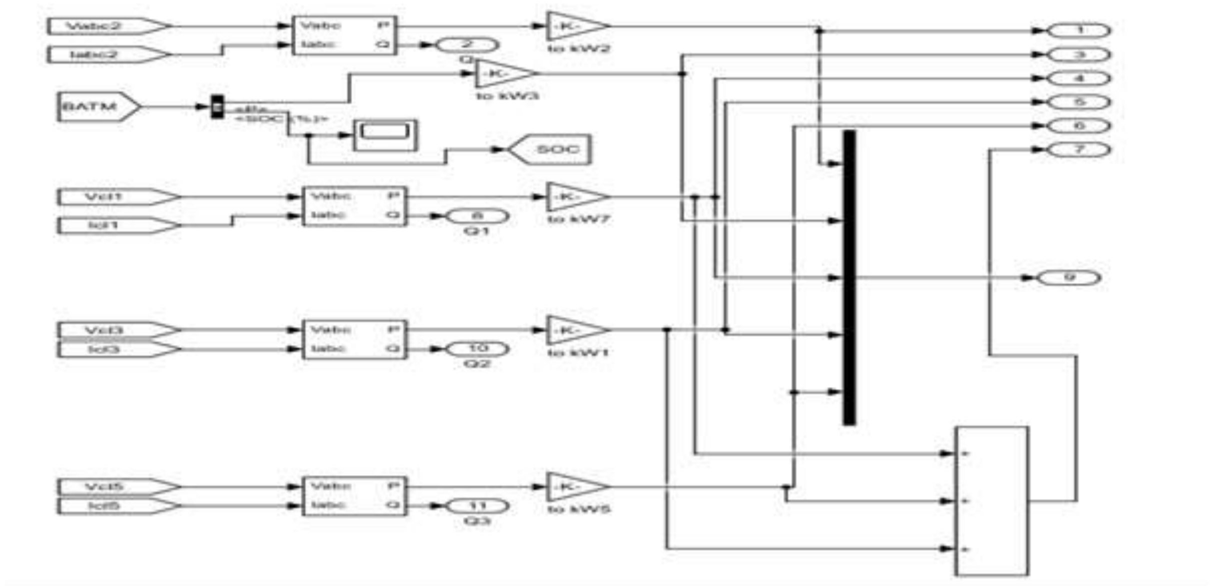


Fig 3 The Block diagram of Energy measurement unit.

The training algorithm that performed better was Levernberg-Marquardt algorithm for it combines the advantages of the Gauss -Newton method and the steepest decent method. It works by iteratively adjusting the network's weights in the direction that reduces the error and was fast compared to other learning algorithms. The algorithm converged to a quadratic error of 6.0254 at 221 steps, indicating a satisfactory level of accuracy achieved during training process and regression close to 1, indicating a strong correlation between the network output and the target values, as shown in figure 7.

RESULTS AND DISCUSSION

After exporting the function fitting neural network to Simulink, two inputs namely the state of charge (SOC) and the time of a day were provided to the network. The output of the neural network is then utilized to control the charging and discharging of the battery. A simulation of the system is then carried over a 24-hour time interval, and the results of simulations are as depicted in the figure 8, showing the comparison of profiles before and after implementing demand side management.

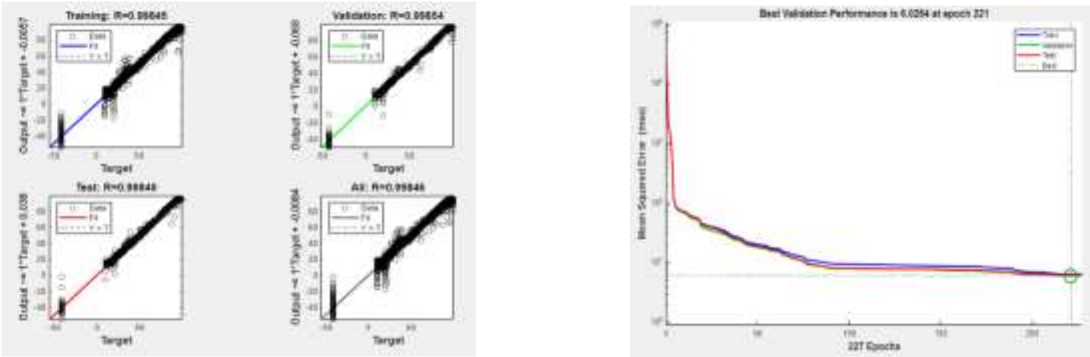
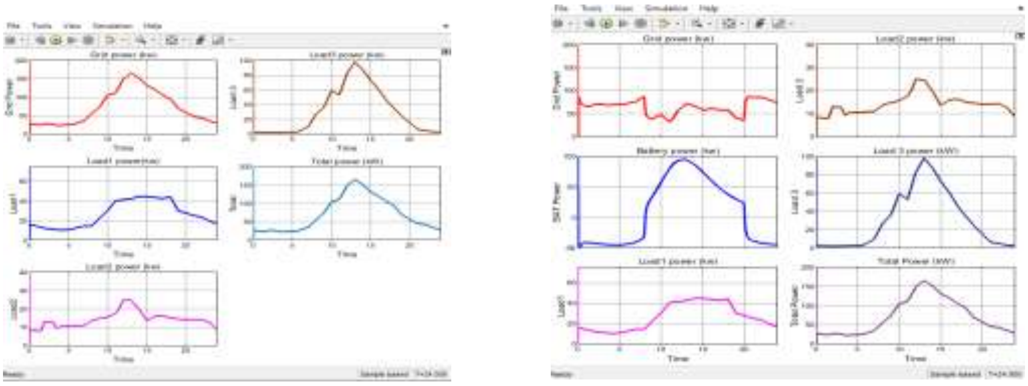


Fig 7 Network training performance and regression plot.



(a) **(b)**

Fig 8 Simulation results for: (a) grid connected load without battery energy storage system and ANN controller; (b) grid connected load with battery energy storage system and ANN controller

From the results above, it is clear that the battery energy storage system clipped the peak loads during peak hour, thus improving the system reliability and efficiency.

The measure of how an electric system's reliability and efficiency are affected by peak electricity consumption is called peak to average ratio (PAR). The PAR in this work is calculated as below and the PAR reduction can be visualized in fig 9.

$$PAR = \frac{Max(Power)}{\frac{1}{24}\sum_{t=1}^{24} Power}, \qquad (2)$$

Before DSM

Max(power)= 165.02kW

$\frac{1}{24}\sum_{t=1}^{24} Power$=70.89694kW

$$\therefore PAR = \frac{165.020}{70.89694} = 2.3276$$

After DSM

Max(power)= 85.645kW

$\frac{1}{24}\sum_{t=1}^{24} Power$=63.2265kW

$$\therefore PAR = \frac{85.645}{63.2265} = 1.3546$$

$$\% \text{ PAR Reduction} = \frac{\text{PAR (Before DSM)- PAR(After DSM)}}{\text{PAR (Before DSM)}} \times 100\%$$

$$= \frac{2.3276 - 1.3546}{2.3276} \times 100\% = 41.8027\%$$

This means the reliability and efficiency of the grid is increased by 41.8027%.

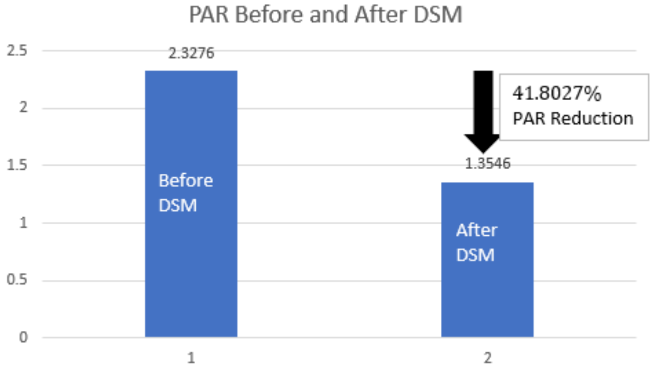


Fig 9 Comparison of PAR before and after performing a Peak Clipping Demand Side Management.

Based on the peak-to-average ratio (PAR) calculations presented above, it is evident that the system incorporating the battery energy storage system with ANN control has significantly enhanced system reliability and efficiency. The PAR reflects the ratio of the peak power demand to the average power demand, and a lower PAR indicates a more balanced and efficient energy utilization. The improved PAR values indicate that the battery energy storage system, controlled by the artificial neural network, effectively manages and smoothens out peak loads, resulting in a more reliable and efficient system overall.

Leveraging DSM in Tanzania's electricity distribution network is a strategic move that can offer numerous benefits. By reducing maximum demand, especially during peak hours and challenging periods like drought seasons, the utility company can enhance grid reliability, minimize load shedding, and mitigate discomfort and losses for consumers and various sectors dependent on electricity. It's a win-win approach that aligns with efficient energy management and sustainable development goals.

CONCLUSION

In conclusion, this study focused on the implementation and benefits of demand side management (DSM) techniques, specifically peak clipping, within the context of Tanzania's electricity distribution system. The research highlighted the vulnerabilities of Tanzania's heavy reliance on hydropower, which makes the grid susceptible to disruptions due to droughts and weather-related events. These challenges have led to energy deficits and necessitated load shedding, causing inconvenience and economic losses for consumers.

The study introduced the concept of DSM as a solution to these challenges, showcasing how a grid-connected battery energy storage system controlled by an artificial neural network (ANN) can effectively manage peak loads. Through the implementation of peak clipping, the system smoothed out peak electricity demand, significantly reducing the peak-to-average ratio (PAR). This reduction in PAR, by approximately 41.80%, translated to enhanced system reliability and efficiency.

The use of ANN in this context allowed for accurate prediction and control of energy demand patterns, optimizing the battery energy storage system's charging and discharging cycles. The simulations demonstrated how DSM can not only mitigate peak demand but also improve grid stability, minimize load shedding, and enhance overall energy utilization.

However, it's important to note that the successful implementation of DSM requires careful consideration of various factors, including customer behavior, regulatory frameworks, and technological feasibility. Additionally, while this study focused on peak clipping, there are other DSM techniques that could further contribute to efficient energy management, such as valley filling, load shifting, and load conservation. To further this study incorporating real-time data and forecasting will enhance the accuracy of the ANN models and improve the efficiency of the DSM strategies by better predicting energy availability and demand patterns. Furthermore, Exploring and implementing more sophisticated control algorithms (Advanced Control Algorithms), such as Model Predictive Control (MPC) or Reinforcement Learning, could improve the system's ability to adapt to dynamic and complex energy scenarios.

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