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Machine Learning – Based Energy Management for Solar and Hybrid Systems with Battery Storage

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Abstract

This paper presents an integrated approach for optimizing grid-connected photovoltaic (PV) systems with battery energy storage, leveraging both Long Short-Term Memory (LSTM) networks for demand forecasting and heuristic optimization algorithms for system sizing. The LSTM model is employed to forecast future electricity consumption based on historical demand data, providing accurate predictions of residential energy needs. These forecasts are then used as input for a heuristic optimization algorithm, such as Genetic Algorithms (GA), to optimally size the PV system and battery storage. The optimisation seeks to guarantee profitability, reduce the discounted payback period (DPBP), and increase system self-sufficiency. The system operates under a time-of use tariff structure, considering scenarios with varying sellback energy prices (off-peak and on peak). Sensitivity analysis is conducted to assess the impact of PV and battery capital costs, as well as discount rates, on the system's economic viability. Results demonstrate that combining LSTM for demand prediction with heuristic optimization can effectively reduce dependency on the utility grid, optimize the system configuration, and achieve substantial cost savings, thus encouraging consumer investment in sustainable energy solutions.

Keywords: Genetic Algorithm, Long Short-Term Memory (LSTM), photovoltaic (PV), discounted payback period (DPBP).

I. INTRODUCTION

One of the most significant renewable energy sources is solar photovoltaic (SPV) energy, which is currently being utilised extensively in distributed generation systems. Applications of SPVs in grid-connected systems and the quick development of SPV technologies show how appealing SPVs are for producing clean electricity for a variety of uses[1]. When an SPV system is connected to the grid, it operates at its Maximum electricity Point (MPP) to supply the grid with the maximum amount of electricity that is available. Because of its availability and ease of use, the traditional Voltage Source Converter (VSC) and interfacing inductor (also known as DSTATCOM) are the most widely used interfacing units in grid-connected SPV system technology. Batteries have advanced as a result of much study, making the concept of a battery energy storage system a commercial reality[2].

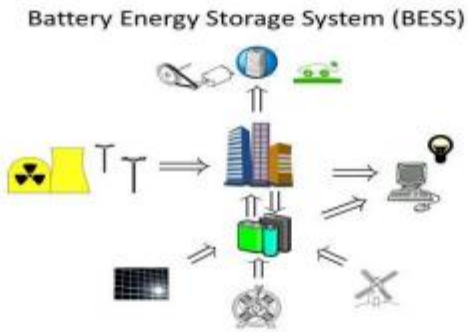

Figure 1: Battery Energy Storage System (BESS)

Usually, a BESS makes use of an electrochemical solution. The systems supplement sporadic energy sources including solar, tidal, and wind power. Because energy storage reduces peak electrical system demand, regional grid market programs frequently provide compensation to ESS owners[3]. Due to its limitless supply and lack of pollution, electricity produced by solar photovoltaic panels promotes local employment and sustainable development. Similarly, it can be used in two ways: either sold to the electrical grid or used in remote areas without a traditional electrical infrastructure. As a result, it works particularly well in rural and isolated locations that are inaccessible by electric power lines, or where installing them is expensive or problematic, and in nations with plenty of sunshine throughout the year[4]. As photovoltaic technology has advanced, the cost of installing and maintaining solar panels—which have an average usable life of more than 300 years—has significantly decreased in recent years. The "fuel" is free and available for life after the solar system is constructed, but there is an initial investment and a minor operating expenditure needed[5,6].

II. SYSTEM DESCRIPTION

The development and use of green technology are aided by rising energy consumption and pollution. Due to its widespread availability PV is adaptable than other forms of energy[7]. During 2013–14, India experienced a transmission and distribution loss of roughly 24.7% of its electricity. Power outages are frequent in India due to a lack of electricity, which has hampered the nation's economic development. The aforementioned factors prompted the purchase of a household photovoltaic (PV) system, which is supported by government subsidies for both the initial installation costs and the long-term financial gains. Optimising the area needed for PV arrays while obtaining the most energy possible from the PV system is the primary issue in installing a standalone PV system (SPV)[8]. As a result, we have optimised the PV system's size in our study. The modules, inverters, direction of PV array, and the inverter's operating characteristics all affect the ideal PV system sizing ratio. For the best PV system design, a multi-objective optimisation that takes into account both technical and financial factors is suggested. This methodology's goal is to maximise system profit while investigating ideal solutions using various optimisation techniques. In recent years, green energy is primary concern in an effort to meet the steadily rising demand for energy and fight global warming[9,10]. Scientists, researchers, and engineers worldwide have been driven to develop new technologies to maximise the energy extracted. Solar energy is the most dependable of all the renewable resources since it is available all day long and silicon, the main component utilised extensively. Various PV models are available for consumers based on how much energy they need. To raise the PV system's voltage and current rating, numerous PV modules are connected to inverters in series and parallel configurations[11]. To get the most power out of the PV modules, inverters use maximum power point tracking, or MPPT. The block diagram of typical PV system is shown below in figure 2.

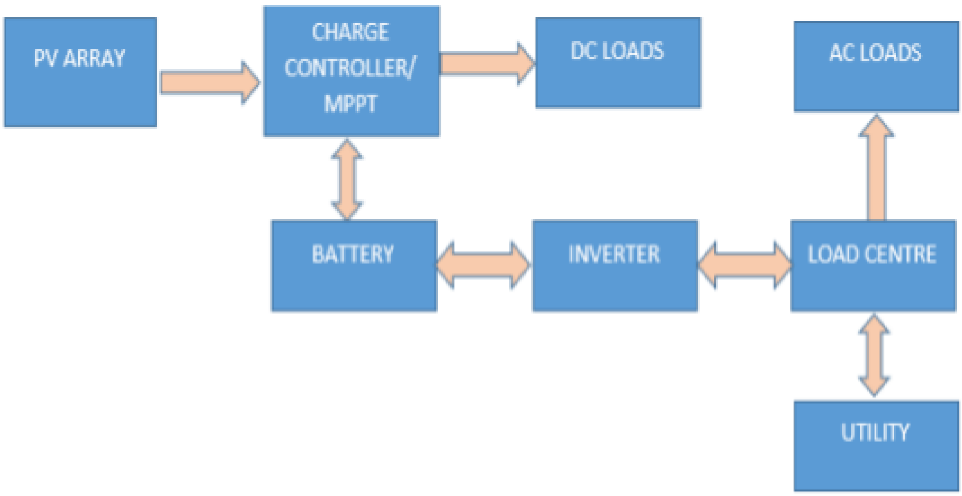

Figure 2: Block diagram of a typical PV system

These (GA, DE, PSO) contemporary stochastic algorithms may tackle real-world problems in order to produce optimal solutions. Therefore, in order to optimise the design of a standalone PV system, each of these algorithms is simulated and compared in this work. The survival of the fittest and natural selection are simulated by genetic algorithms[12]. GA is a search technique used to locate rough answers for optimisation issues. The individual is defined by a collection of parameters that need to be optimised, and the population is made up of a set of individuals that change over time as a result of crossover, mutation, and selection. This algorithm first generates a random population or set of solutions, after which its fitness is assessed. The individuals are then chosen for reproduction based on their fitness. After that, the chosen individuals go through crossover and mutation processes to produce progeny, which make up the population of the following generation. Figure 3 displays the fundamental GA algorithm. Each chromosome shows numerous parameters and a potential solution to the optimisation challenge. Three parameters are included in the current work, including, $x = [NPV|N|\beta]$. The best people are reproduced through selection based on fitness values. The greater the fitness value, the greater the likelihood of selection. Georgia uses a variety of selection techniques to choose the best candidate, including the following:

- Selection of the roulette wheel
- Stochastic-based selection
- Tournament selection
- Reward-based selection

Since the roulette wheel selection approach assigns chromosomes a probability of being selected that precisely matches their fitness, it is used in the current work. Based on these probabilities, two chromosomes are then randomly selected to create children. In order to eradicate weak solutions and ensure that strong solutions endure for the following generation. The binary representation of the chosen chromosomes or solutions prior to crossover operation consists of strings. By combining segments of any two current-generation parents, crossover operations produce two solutions. For simplicity, single point crossover is used in this work. We now have a new generation following selection and crossover, some of which are formed via crossover and others of which are directly duplicated. The next stage is to allow for a slight probability of mutation to make sure that the people are not all precisely alike. Only a small number of people from the new generation are selected at random in this step. This selection process is carried out using uniform probability rather than its fitness value. From each chosen chromosome, a random bit is chosen and flipped to its corresponding value (0 or 1). Compared to crossover operations, mutation operations are more random and have a far lower probability. Nevertheless, it is carried out because it might contribute to the development of a useful trait that the current generation lacks. Typically, the likelihood of mutation falls between 0.001 and 0.002. After the maximum number of iterations has been generated, the algorithm stops evaluating the new population.

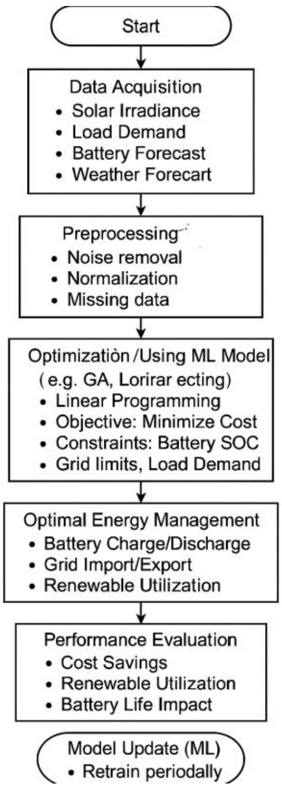

Figure 3: Flowchart for Optimization Algorithm

The rand is a random number between 0 and 1, and the current position of the particle at the (m+1)th and m^{th} iteration is represented by p(m +1) and p(m). A random position and velocity are used to initialise the population. The population's fitness is then assessed and contrasted with earlier p_{best} and g_{best}. Where necessary, their positions are revised. Thus, a new population or swarm is formed. Until maximum generations or convergence are attained, the position and velocity are updated. The PSO algorithm has several key advantages over other approaches, including the fact that no derivative calculation is necessary, that all particles hold the information about the optimal solution, and that those particles provide data among themselves. Because the PSO algorithm requires no initial solution and only a few control parameters, it is simple to program[13]-[14].

Whether an optimisation problem is confined or unconstrained, GA is a frequently used technique to address it. It produces a number of points known as the population at each iteration. The point in this population that is closest to the ideal solution is the best point. Because of its accuracy in identifying the best solution, GA gained popularity as a solver and garnered a lot of interest for optimisation issues.

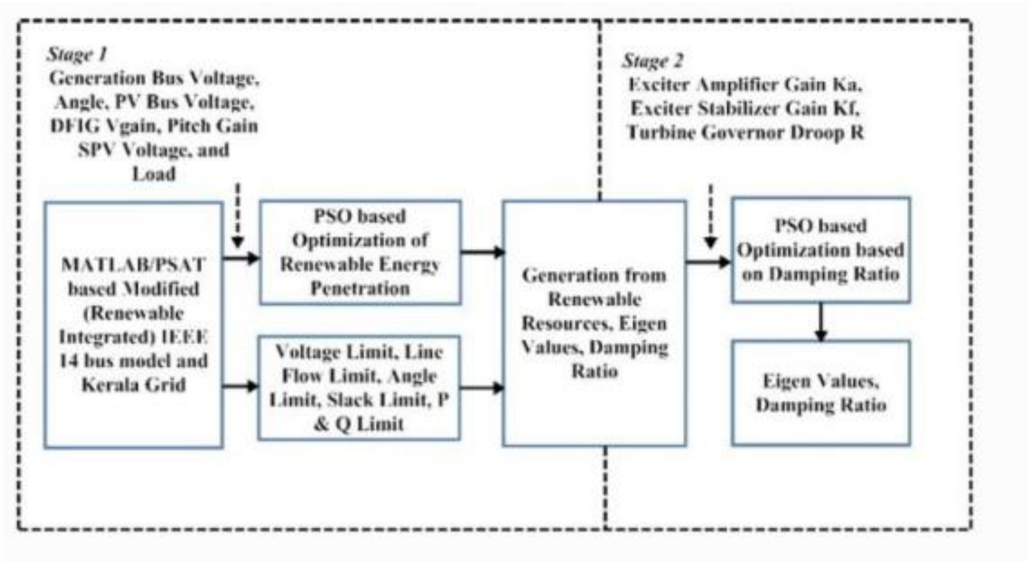

Figure 4: Existing Block Optimization Algorithm

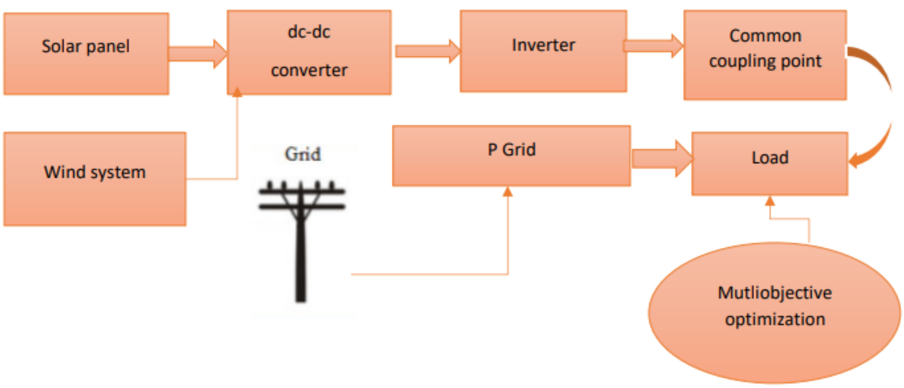

Figure 5: Proposed Block Diagram

As illustrated in figure 5, the PV arrays, DC/AC converter, and utility grid make up the PV grid-connected system taken into consideration in this work. Solar energy is captured by the PV arrays and transformed into direct current (DC) electricity, or Ppv. After receiving the DC power, the DC/AC inverter transforms it into an alternating current (AC) power source, Pinv. There is no auxiliary power conditioning device between the loads and the utility grid; they are both directly connected to the common coupling point. This study employs a bi-objective optimisation technique for BESS sizing in order to assess the optimal trade-off between increasing BESS capacity and improving REC self-sufficiency, while allowing DSOs to use BESSs widely. While the latter is the primary factor influencing BESS deployment costs, the former is also a measure of potential economic and environmental advantages. We will be able to determine the feasibility and profitability of BESS deployment by calculating the Pareto front of non-dominated solutions under various operational settings and scenarios. Let's assume that all grid users linked to the same substation are considered members of the same REC for simplicity's sake without sacrificing generality. Not all prosumers may be interested in installing a BESS, but they are all already outfitted with a PV generator. Bidirectional power flows may take place within the REC across the distribution system's lines, and the transformer's secondary winding in the substation that connects the REC to the main grid may occasionally receive the reverse power flows. The excess power generated can be fed into the grid under these circumstances, which arise whenever the PV power surpasses the entire load demand and cannot be held in the BESSs. Using a multi-objective optimisation method for system sizing and Long Short-Term Memory (LSTM) for demand forecasting, this article attempts to design and optimise a grid-connected photovoltaic (PV) system with battery storage to satisfy the electricity demands of residential consumers. The main objectives are to minimise the Discounted Payback Period (DPBP), lower annual electricity expenditures, and increase efficiency & capacity to meet demand for electricity independently of the utility grid. One or more horizontal-axis wind turbines (HAWTs), which are intended to transform kinetic wind energy into electrical energy, make up the wind energy system in the suggested hybrid renewable configuration. Site-specific wind speed profiles, which are obtained from local wind monitoring systems or historical meteorological data, are used to choose these turbines. To guarantee effective energy conversion and grid compliance, the wind turbines are integrated with a power conditioning unit that consists of rectifiers, inverters, and maximum power point tracking (MPPT) controllers. Converting the kinetic energy of wind into mechanical energy and then electrical energy is the basic idea behind wind energy conversion.

A solar panel, wind turbine, battery storage, and a dynamic load coupled by a microgrid are among the integrated parts of the simulation circuit. The battery controls energy balance during variations in generation or demand, and the system simulates power flow between sources and loads. Stable operation and efficient energy use are guaranteed by the microgrid controller. In reaction to available electricity from battery storage and renewable sources, the dynamic load controller modifies the load demand. By giving priority to vital loads during periods of low generation and lowering or moving non-critical loads to preserve system stability, it guarantees load balancing.

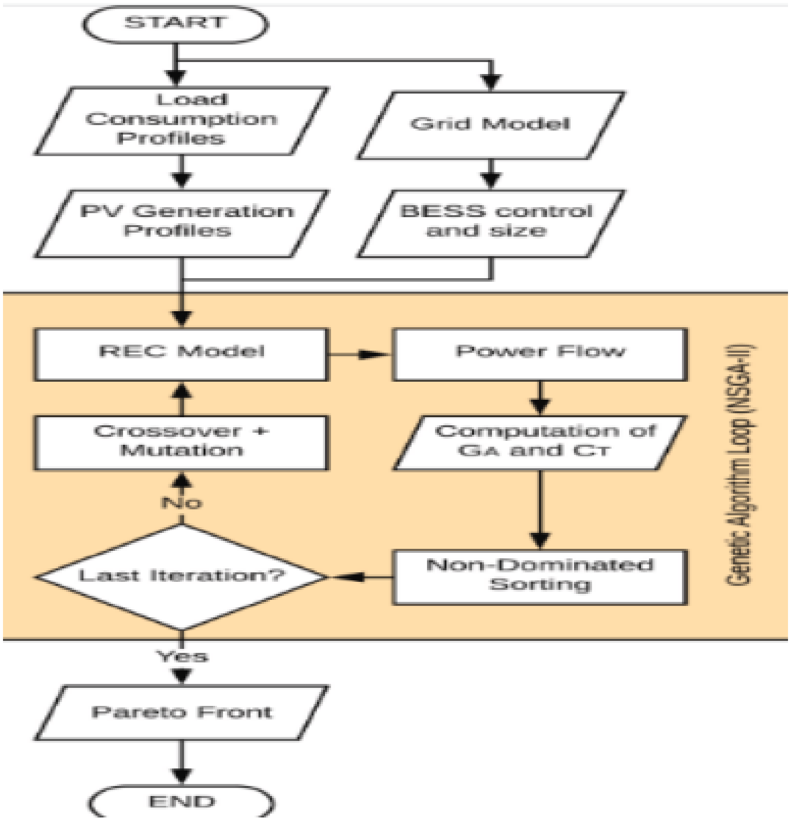

Figure 6: Multi Objective Optimization Algorithm

III. Software Implementation

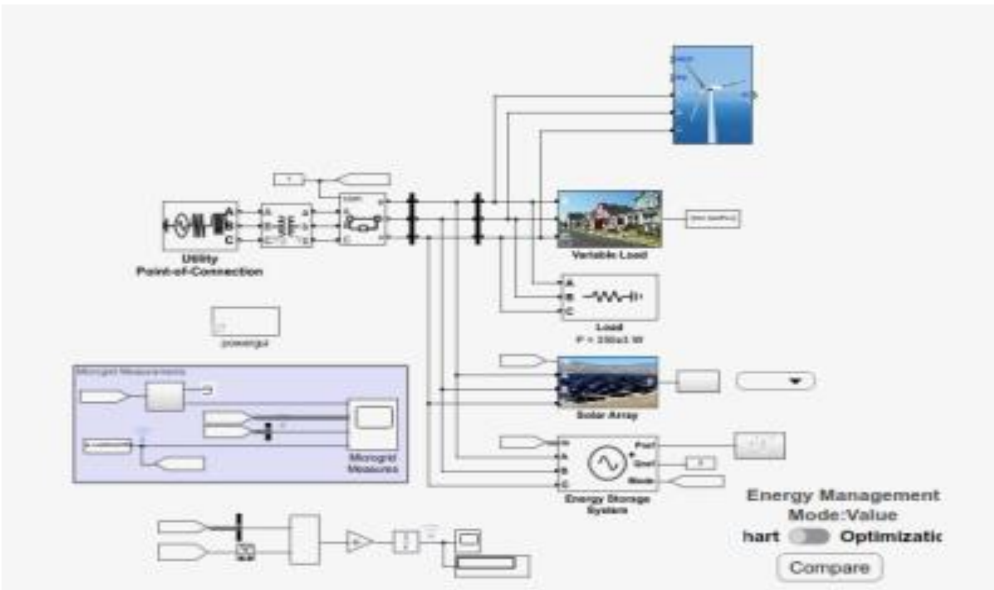

Figure 7: Solar and Wind with Grid system

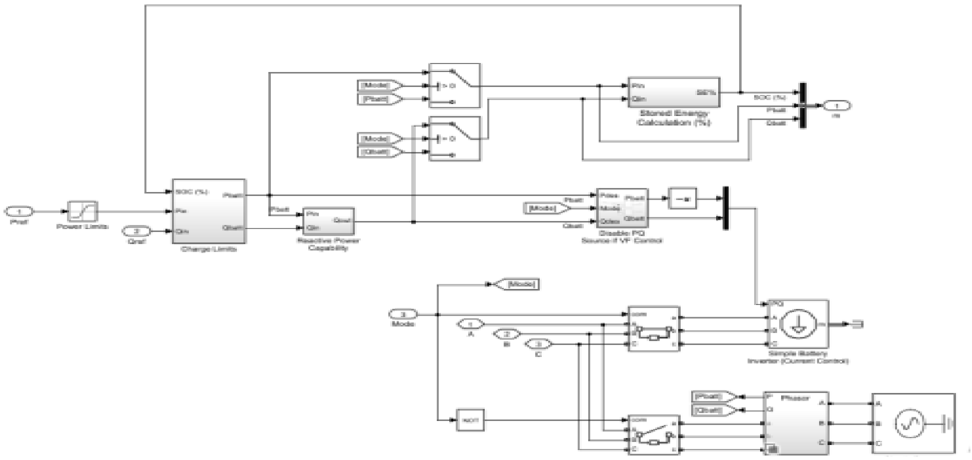

Figure 8: Controller of Dynamic Load

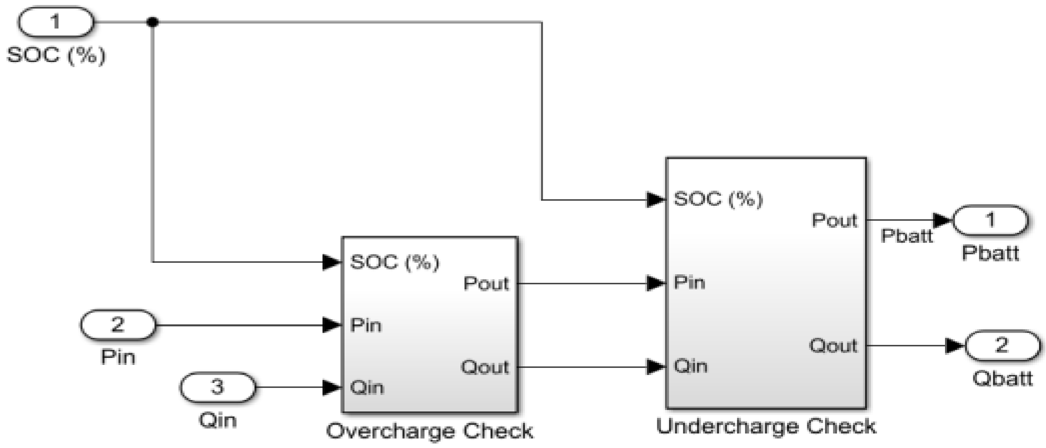

Figure 9: Over voltage and Under voltage Controller

Real-time system voltage level monitoring is done by the over-voltage and under-voltage controlling circuit, which also triggers protective measures when thresholds are surpassed. In order to prevent equipment damage and guarantee stable functioning of the hybrid energy system, it disconnects delicate components during abnormal voltage situations. Depending on energy availability and demand, the system management circuit is in charge of switching and routing power to the grid or to the battery for charging. In order to guarantee effective energy transfer, avoid overcharging, and maximise grid interaction, it makes use of control logic or relay-based techniques. Real-time adjustments are made to the 3-phase dynamic load according to the hybrid system's power availability. In reaction to fluctuating energy supplies, it can alter the characteristics of its load, guaranteeing optimal use and preserving system stability. By incorporating resistive, inductive, and capacitive components into the circuit, the RLC load (Resistive, Inductive, and Capacitive) replicates real-world load behaviours. In order to evaluate how the system responds to various load conditions and power factors, this kind of load is frequently used to mimic both reactive and real power consumption.

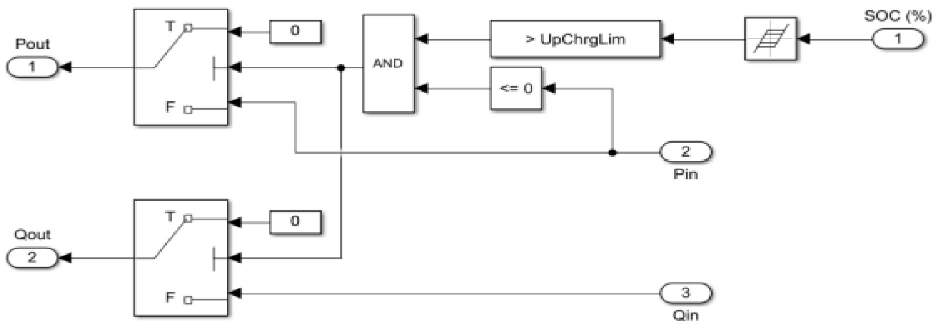

Figure 10: Controller of the System

IV. Simulation Output and Result

Variations in voltage across the grid, solar, wind, and battery components are displayed in the simulation output. The strength of the sun affects solar voltage, which peaks in the middle of the day and falls in overcast weather. Wind speed and turbine performance have an impact on wind voltage. In order to keep the system within safe bounds, battery voltage varies according to cycles of charging and draining. When renewable energy production is low, the grid voltage serves as a backup source of power and stays constant. In order to preserve system stability and maximise energy flow, these voltage fluctuations are effectively controlled.

Heuristic EMS Cost: $ 915.5301
Optimization EMS Cost: $ 756.5504
Difference (%) between Methods: -17.3648%

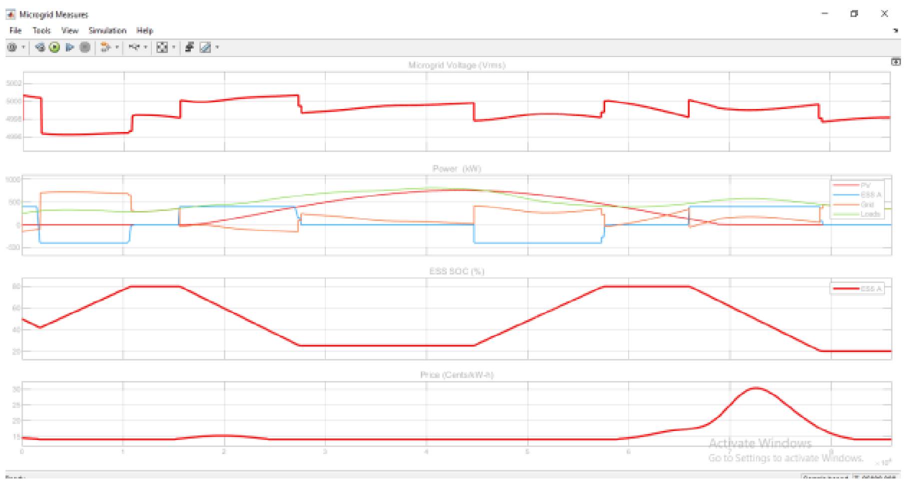

Figure 11: Microgrid voltage and BESS voltage

Following the implementation of heuristic-based optimisation, the final cost result demonstrates a notable decrease in the whole system costs, including those associated with energy generation and storage. By effectively balancing the use of solar, wind, batteries, and the grid, the optimised values reduce operating costs while guaranteeing stability and a dependable energy supply. The optimisation strategy methodically determines the most efficient solution by taking into account all potential variables and restrictions, making it more cost-effective than heuristic methods. The ideal balance between energy generation, storage, and grid interaction is frequently missed by heuristics, despite the fact that they offer effective solutions fast. However, by precisely balancing the usage of storage and renewable sources, optimisation guarantees low operating costs, which eventually results in lower system costs overall.

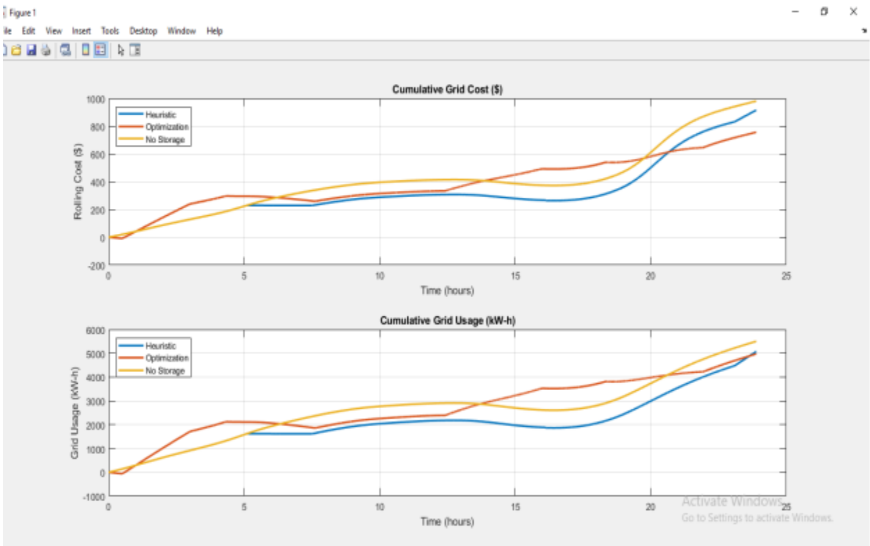

Figure 12: Grid usage and rolling cost analysis

V. CONCLUSION

To ensure good performance, the optimisation was exposed toward the necessary technical and financial constraints. Two energy scenarios were considered under which the optimisation was suggested. As a result, optimisation was created to help accomplish both goals. To ensure profit, the optimisation was subjected to exposed toward the necessary technical and financial constraints. 77.4% system self-sufficiency and a 9.9-year discounted payback period are achieved with a 20 kWp photovoltaic system and a 16.8 kWh battery system. Without batteries, a 20 kWp PV system can achieve 46.7% self-sufficiency with a minimum discounted payback period of 2.4 years. Adding a 57.6 kWh battery increases self-sufficiency to 99.3% with a ten-year payback period. Sensitivity analysis showed that reducing PV or battery capital costs boosts profitability and allows for increased battery use without violating system constraints.

References

[1]. H. Yang, Z. Gong, Y. Ma, L. Wang, and B. Dong, ‘‘Optimal two-stage dispatch method of household PV-BESS integrated generation system under time-of-use electricity price,’’ Int. J. Electr. Power Energy Syst., vol. 123, Dec. 2020, Art. no. 106244.

[2]. J. Chen, X. Jiang, J. Li, Q. Wu, Y. Zhang, G. Song, and D. Lin, ‘‘Multistage dynamic optimal allocation for battery energy storage system in distribution networks with

photovoltaic system,'' Int. Trans. Elect. Energy Syst., vol. 30, no. 12, 2020, Art. no. e12644.

[3]. S. Korjani, A. Serpi, and A. Damiano, ''A genetic algorithm approach for sizing integrated PV-BESS systems for prosumers,'' in Proc. 2nd IEEE Int. Conf. Ind. Electron. for Sustain. Energy Syst. (IESES), Sep. 2020, pp. 151–156.

[4]. W. S. Vaz, ''Multiobjective optimization of a residential grid-tied solar system,'' Sustainability J., vol. 12, pp. 1–15, Oct. 2020.

[5]. A. H. Razali, M. P. Abdullah, M. Y. Hassan, D. M. Said, and F. Hussin, ''Integration of time of use (TOU) tariff in net energy metering (NEM) scheme for electricity customers,'' Indonesian J. Electr. Eng. Informat. (IJEEI), vol. 7, no. 2, pp. 255–262, Jun. 2019.

[6]. J. Li, ''Optimal sizing of grid-connected photovoltaic battery systems for residential houses in australia,'' Renew. Energy, vol. 136, pp. 1245–1254, Jun. 2019. 55

[7]. U. G. K. Mulleriyawage and W. X. Shen, ''Optimally sizing of battery energy storage capacity by operational optimization of residential PVbattery systems: An australian household case study,'' Renew. Energy, vol. 160, pp. 852–864, Nov. 2020.

[8]. M. Najafi Ashtiani, A. Toopshekan, F. Razi Astaraei, H. Yousefi, and A. Maleki, ''Techno-economic analysis of a grid-connected PV/battery system using the teaching-learning-based optimization algorithm,'' Sol. Energy, vol. 203, pp. 69–82, Jun. 2020.

[9]. P. B. Asare, I. E. Davidson, and D. B. S. Simatele, ''Machine learning techniques for energy management in smart grids with renewable energy resources: Recent advances, challenges and future directions,'' Renew. Sustain. Energy Rev., vol. 137, p. 110618, Mar. 2021.

[10]. Y. Zhang, N. Gatsis, and G. B. Giannakis, ''Robust energy management for microgrids with high-penetration renewables,'' IEEE Transactions Sustainable Energy, vol. 4, no. 4, pp. 944–953, Oct. 2013.

[11]. N. Javaid, I. Khan, M. Imran, M. M. Khan, A. Alrajeh, and M. Guizani, ''A review of energy management strategies for smart homes,'' Energy Rep., vol. 6, pp. 2903–2920, Nov. 2020.

[12]. M. Ghofrani, A. Arabali, M. Etezadi-Amoli, and M. S. Fadali, ''Smart scheduling and cost-benefit analysis of grid-integrated energy storage,'' Applied Energy vol. 119, pp. 343–353, Apr. 2014.

[13]. H. Rastegar, M. Fotuhi-Firuzabad, and H. Zareipour, ''Home energy management incorporating operational priority of appliances,'' International Journal of Electrical Power Energy System, vol. 74, pp. 286–292, Jan. 2016.

[14]. K. Muthuvel, P. Muthukumar and Thomas Thangam, Forecasting Solar Power Generation with Machine Learning Techniques, ARPN Journal of Engineering and Applied Sciences, VOL. 19, NO. 22, November 2024.