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AI-Enhanced Energy Management Systems for Efficient Flow Control in Microgrids

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ABSTRACT

This paper has presented a new approach for investigating the potential to rationally use promising sustainable energy sources with highly developed energy management systems integrated into IoT and AI technologies. The empirical analysis was done through a Genetic Algorithm model in Python taken on a typical microgrid system that supplied power to 100 homes at an average of 47 kW. The simulation results show an enormous reduction of waste power in the order of 93%, but at a costlier overall in the microgrid, up by approximately 25%. These results act as strong proof that this integrated approach is technically feasible and economically feasible for the pursuit of efficiency and savings. This study goes further to consider the economic implications of the implementation and maintenance of EMS. It also considers cybersecurity as one of the critical challenges in interconnected microgrids that might influence operational integrity. The research further contributes significantly to knowledge on battery consumption loss and the factors that have to be addressed to avoid negative impacts on the overall system. This research considers a microgrid as a key building block in a flexible and resilient energy infrastructure; its approach covers more than just technical discussions but fosters a broader, transdisciplinary dialogue. In the future, smart EMS integrated with IoT and AI is foreseen to be necessary to enable microgrids to maintain a sustainable and reliable power supply in communities. In short, this article gives fresh guidelines for the development of energy systems that are bound to be not only more efficient but also stable enough to resist any challenge that may come from environmental dynamics. Finally, the article calls upon all researchers, policymakers, and other stakeholders to contribute their quota in shaping the future of energy systems of the 21st century in a way that can help make the energy landscape more sustainable and resilient.

1 | Introduction

In this vast and elaborate web of energy dynamics, a microgrid turns out to be a strong fortress that dares to question the very core of the conventional power distribution system. Such small domains of energy self-sufficiency, nourished on indigenous resources, are beckoning us toward such an era when sustainability and energy self-sufficiency are inextricably tied in an exquisite symphony [1]. Yet, the untapped potential of microgrids cries for orchestration through the painstaking design of sophisticated energy management systems (EMS) [2]. Our work tells the story of a journey to navigate through the complex landscape of microgrid optimisation, charting a path to that horizon in a world confronted with an ultimate fusion of IoT

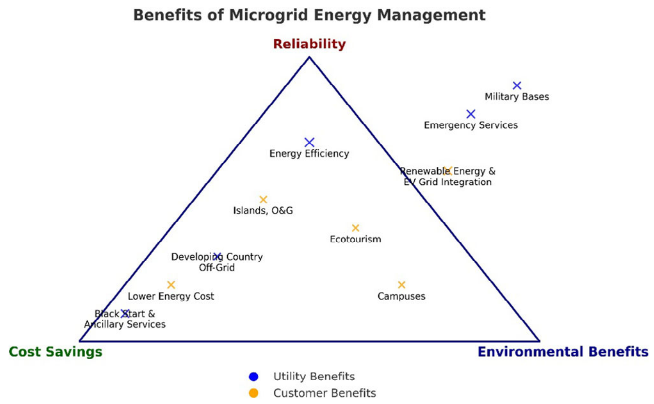

FIGURE 1 | EMS role between utilities and customer benefits.

and AI, where the very capabilities of EMS are gathering full momentum and rewriting the very fundamentals of our energy future [3].

At the heart of our narrative is a twin mandate euphemism for an exquisite balancing act between reducing operational costs and responsibly minimising carbon emissions. In a world where economic prudence finds its meeting point with ecological sensitivity, microgrid optimisation becomes a very viable proposition-an ethereal ballet, powered by the blissful coming together of IoT and AI. This convergence is not a simple question of aligning technological facets; it is a strategic ballet choreographed spectacle that harmonises disparate goals, forging a path toward economic prosperity and ecological stewardship, as in Figure 1 below [4].

We are past the simple technicality of a journey; it's an orchestration of flux energies within microgrids. Beyond the basic need to have a steady supply of power, the effort now moves into those more sublime regions where efficiency would be at its optimum and the balancing act of environmental damage is at its best. It is anything but a linear journey; rather an immersive plunge into the multilayered challenges, nuanced benefits, and transformative potential that this fusion of IoT and AI has brought about in the already intricate world of microgrid energy management. The optimisation of microgrids draws a very idealistic picture of sustainability from their stand at the nexus where innovation intermixes with environmental stewardship. In fact, this is not a gesture but an unflinching commitment to having a future whereby technological prowess thrusts us toward economic prosperity without betraying the delicate ecological balance of our planet's sole dwelling place.

Python rises above its utilitarian beginnings within our toolset to be the maestro orchestrator of our methodology. Python has grown beyond merely being a language of programming; with it, the true artist paints in the fine details of the microgrid model and the algorithms of the EMS with strokes of elegance and adaptability. Simulations with Python are not aseptic exercises but thriving colonies capable of intelligent adaptation to the dynamics underpinning variable energy demands and supplies [5, 6].

We now embark on this great adventure, engaging in a request for your serious participation in the process of managing this rich tapestry, which is the optimisation of energy flux in microgrids.

Far beyond a technical paper, this is a serious redefinition of possibilities that open at a juncture where sustainability and computational powers meet at their zenith. Let us walk the path together where the Python code would represent the baton of the conductor so that the symphony of efficiency and responsibility could march towards that future wherein innovation once more turns into a commitment and not a means towards a paradigm of sustainable, efficient, responsible energy. In this epic article, innovation and responsibility are intertwined in a tale of advancement and thoughtful care within the realm of energy management. The sections that follow delve deeper into many of the layers around microgrid optimisation and further reveal the potential to transform the forging for a more sustainable and resilient energy future for generations to come [7, 8]. The following sections outline an overview of how energy flow management can be optimally done in microgrids.

Section 2 reviews the essentials of microgrid energy flow optimisation; thus, it also forms a very good basis on which our work could rely. This is followed by Section 3, which describes our contribution to the work in terms of mathematical and algorithmic modelling; therefore, it furnishes the axes of our approach. Section 4 goes deep into the dynamic management of energy contribution, while the role of AI and IoT puts the core in underlining the main contribution these technologies bring about in terms of efficiency and performance to microgrids. Conclusions and Final Remarks: After the presentation of results, Section 5 will introduce our simulation of an example of an islanded microgrid with a load of 100 houses and interpretation of results with future perspectives. This section describes the interpretation of the results of simulations, extending some future perspectives and directions for possible research. In return for that respect, our approach will be structured to develop a comprehensive yet valuable analysis of microgrid optimisation for the researchers, policymakers, and stakeholders in energy management.

2 | Microgrid Energy Flow Optimisation Fundamentals

2.1 | EMS in a Microgrid

EMS play a key role in dynamically optimising energy generation, distribution, and consumption within a microgrid. The main goal is to guarantee, together with the efficiency and reliability of energy supply, minimum cost and environmental impact, as can be seen in Figure 2.

The sensors, among other components, form the centre of the web in the intricate web through the provision of real-time data related to energy production and consumption as well as grid conditions. This capability for real-time monitoring forms the bedrock of the EMS, enabling it to make informed decisions based on current energy demand and supply conditions [9, 10].

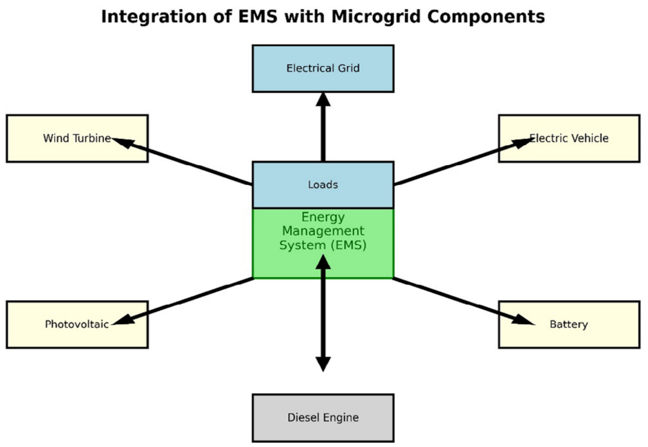

FIGURE 2 | EMS in microgrid.

The control algorithms constitute the EMS intelligence. These algorithms provide the brain of how a microgrid operates: the way energy sources are called upon, when to charge or discharge the energy storage system, and how to react to unforeseen disturbances on the grid. The communication infrastructure allows seamless coordination amongst the various components that are able to provide quick responses to the change in energy demand or the availability of renewable sources, as depicted in Figure 2 below.

This becomes one of the major strategies in EMS, and all energy sources are categorised into this. Priority goes to renewable sources when available, such as solar or wind power. It may be because of algorithmic approaches to make decisions on the optimum use of available sustainable energy sources considering real-time data and weather forecasts. In addition, the batteries play the role of strategic components for energy storage controlled by EMS algorithms that are directed toward optimising charge/discharge cycles for maximum efficiency and lifespan. Biomass becomes a reliable backup when the generation of renewable energy is fluctuating or in case of a sudden disturbance in the grid. EMS algorithms optimise the deployment of biomass resources, considering a range of issues related to cost-effectiveness and environmental impacts. This multidisciplinary prioritisation strategy offers continuity in power supply with stability in variable conditions.

Adaptive decision-making represents one strong point in the operational capability of EMS. It naturally reacts dynamically in real time to energy demand and supply fluctuations, including unexpected events, through algorithms that constantly update. Some advanced EMS systems include machine learning that allows the performance to improve based on historical data and evolving grid conditions.

User interaction and transparency go hand in hand with the assurance of optimum performance by the EMS. By this premise, the system interface will be user-friendly enough to keep the stakeholders engaged through an understanding of the operating status of the microgrid. By implication, this interface is transparent; hence, users understand how the EMS will work as well as the consequences of the decisions of its operations on energy utilisation and costs [11, 12].

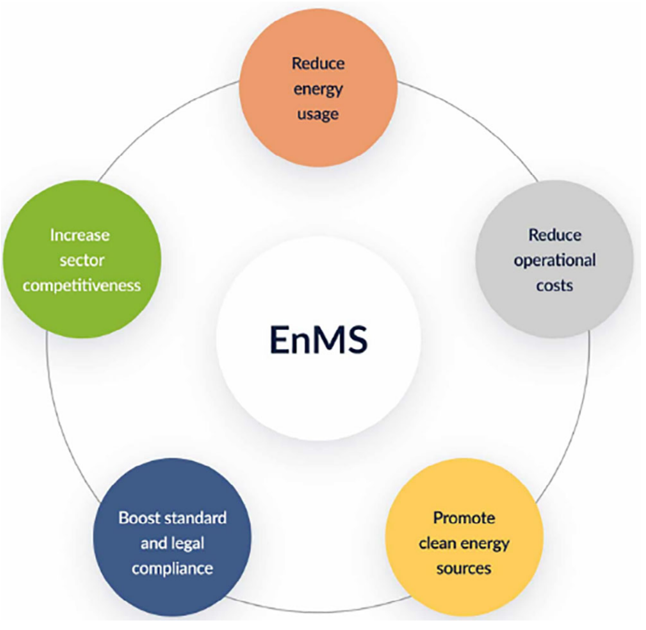

FIGURE 3 | Energy benefits of an EMS.

One of the most important roles of EMS is optimisation for cost-cutting and mitigating emissions. As a matter of fact, EMS itself is designed to optimise energy use by focusing on reducing operational costs that contribute to carbon emissions reduction and meeting sustainability goals accordingly [12].

Looking ahead, scalability remains an important factor: the EMS has been designed to support the addition of extra renewable sources, batteries, or higher technological levels. The modelling tool used is Python, which gives the added advantage that new components and algorithms can be added and utilised for microgrid requirements in the near future with minimal changes [12, 13].

Conclusion In other words, EMS in microgrids stands for a dynamic, adaptive system that performs intelligent management of energy resources. Since it reduces environmental impact and effectively increases efficiency in demand satisfaction, this system bears great relevance to the future of microgrid management, wherein continuous developments in advanced algorithms and machine learning, together with the integration of emerging technologies, occur regularly.

2.2 | Energy Flow in a Microgrid

Energy flow management is basically the key behind any microgrid for the purpose of overall performance optimisation and assurance of a reliable power supply. In this context, according to the above rules, the energy flows in a microgrid can be divided into three categories that include energy produced, energy consumed by the load, and energy stored in batteries. The EMS is at the centre of orchestrating these elements to make prudent decisions on when to store energy, use battery power, or resort to alternative sources like biomass for backup to satisfy the main benefits as shown in Figure 3.

The first produced energy component involves electricity generated from various sources in the microgrid, such as solar panels, wind turbines, or any other distributed generation systems. Their availability and output will be continually monitored by the EMS to know the total energy production potential.

Energy consumed by the load is the amount of electricity demanded by the consumers and the respective devices being used within the microgrid. The demand patterns, load profiles, and real-time consumption data are assessed by the EMS to understand when energy is needed and how much of the same would be required [14].

The energy stored in the batteries forms a very critical element of resilience and flexibility in the microgrid. This, while energy is charged or discharged from the batteries at different rates, forms the basis of decisions made by the EMS to determine if a certain amount of energy needs to be stored in the batteries for later use or to release the stored energy during peak demand periods.

The inclusion of supercapacitor and flywheel models in the EMS reflects their role as auxiliary storage components to enhance system stability. Supercapacitors provide rapid energy discharge for short-term power demands, while flywheels offer mechanical energy storage that complements the battery system. These models were incorporated into the optimisation framework to ensure that their characteristics, such as charge/discharge rates and efficiency, were accurately represented. Simulation results demonstrated that these technologies significantly reduced the strain on primary storage systems during peak loads.

Through such a process, complex algorithms and predictive models apply to various parameters, including energy prices, grid conditions, and environmental factors. For instance, when the production of renewable energy is high and energy prices are very low, the EMS will give priority to using excess energy first in storing it in batteries for use in the future. On the other hand, it may be such that in periods of peak demand or when the renewable sources are limited, the system may decide to use the energy stored in batteries or initiate backup sources from biomass to supply the requirements of the load [14, 15]. In a word, the EMS is a potent controller that manipulates the energy produced, consumed by the load, and stored in batteries with great foresight. The EMS balances the three entities mentioned above dynamically to achieve optimality in energy utilisation, cost-effectiveness, and reliability within the microgrid for a sustainable and resilient energy infrastructure [15].

2.3 | The Necessary Inputs of an EMS

The good functionality of an EMS in microgrids, besides monitoring and managing the energy flow, also takes into consideration several external factors such as energy market prices, weather conditions, and estimated load demand. These additional parameters ensure that the decision of the EMS is critical in making informed and optimal choices regarding energy production, consumption, and storage, as shown in Figure 4:

Energy market price is considered one of the most important inputs to an EMS since it drives all the economic aspects of managing energy. The system will therefore need to evaluate real-time or forecasted prices for assessing the cheapest time of energy usage, storage, or even selling back to the grid. Given the consideration in the market dynamics, the EMS will be able to assist a microgrid operator in minimising the operational cost by optimising revenues [16, 17].

Other major factors that have impacts on these two renewable sources of energy supply are weather conditions. The EMS will receive weather forecasts and current meteorological data in order to update the changes likely to be witnessed by renewable energy generators. This will be important in giving a fair warning on when the energy supply is going to be low or high so that control can be effected on the microgrid operation. The EMS can then stress battery storage or turn on other sources if a cloud cover is forecasted to lower solar generation [17]. The forecasted load demand is, therefore, one of the most important parameters for the EMS to enable the microgrid to meet the energy demands of its users. Through a study of historical consumption patterns, the system is able to forecast future load demands supported by real-time load monitoring. Such foresight enables the EMS to actively manage the energy resources well in advance in order not to encounter an insufficient supply or an unnecessary excess.

This means incorporating advanced algorithms and predictive modelling in the decision-making process of the EMS in these external factors. The balance among economic considerations, environmental conditions, and user demand needs to be economically optimised so that energy use and storage can be optimal. Dynamic market prices, weather patterns, and shifting load demands must be dynamically adjusted by the EMS toward the overall efficiency, reliability, and sustainability of the microgrid.

In other words, in an effective EMS in microgrids, energy flow management considers energy market prices, weather conditions, and estimated load demands. As such, a holistic approach makes the microgrid act optimally, responding both internally and externally toward taking part in a resilient and adaptive infrastructure of energy [16, 17].

2.4 | EMS Algorithm

The setting of priority among energy sources is the most important feature in the EMS of a microgrid to enable its running in an efficient and sustainable manner. The EMS follows a hierarchical approach whereby renewable energy sources are taken as the first priority that would help to supply the dynamic load demand; mainly, wind and solar power are considered the base contributors. First, it harvests the energy provided by the wind turbine and solar panel, which are computed based on the prevailing wind speed and solar irradiance. In a case where the combined renewable energy production is enough to satisfy the prevailing load demand, the EMS guarantees that all renewable energy available is utilised so as to maximise the usage of clean resources [12, 13, 18]. With partial demand coverage by renewable energy, the EMS intelligently deploys energy storage capability in the batteries. Energy stored in the batteries acts as a secondary source for filling the demand gap left by renewable energy production. This two-tier approach makes sure that renewable energy use is optimised, thereby reducing

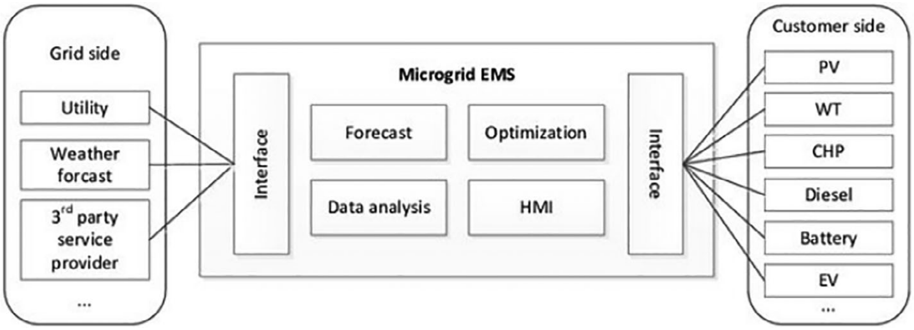

FIGURE 4 | EMS interaction with microgrid elements.

dependence on non-renewable sources to an absolute minimum [1, 2].

Furthermore, if at any instant the generation of renewable energy surpasses demand, the immediate actions taken by EMS make the entire system resilient and efficient. The excess energy is stored in the batteries for future demand or, in the case of fully charged batteries, the extra energy is intelligently evacuated using a dump load. The dump load acts as a protection mechanism to avoid overcharging of the batteries and maintain stability in the microgrid. This strategy works at an optimum in energy storage and sees that no renewable energy resource goes to waste, hence enhancing a sustainable and eco-friendly energy management approach [6]. In those situations, when renewable energy and battery storage cannot cover the demand load, biomass is used as a backup source; the transition to that could be seamlessly integrated via the EMS.

Biomass power, too, is a fallback, and, as such, it plays a vital role in the continuity of energy supply and hence the reliability of the operation of the microgrid. It, therefore, means that dynamic prioritisation performed by the EMS manifests a commitment to the fullest utilisation of renewable resources while intelligently managing energy storage and backup sources in order to ensure a robust and resilient energy supply under all regimes of operations [14–16].

This study, mainly, has focused on developing an energy management strategy aimed at the minimising energy waste. The energy dumping, in this context, defines the surplus energy created on top of what was utilised and saved when supply exceeds demand. Therefore, by reducing the amount of dumped energy, the system ensures not only a boost of efficiency but also directly contributes to cost reductions within operations. GAs are best suited for this problem because they can optimise the complex nonlinear relationships that are inherently part of the EMS. GAs can efficiently explore and exploit solution spaces to attain minimum wastage with cost-effectiveness, thus being optimal for this multi-faceted problem.

3 | Mathematical and Algorithmic Model

3.1 | Renewable Power Generation

The output power of the turbine is given by the following Equation (1):

$$P_w = C_p\ (\lambda, \beta)\ (\rho * A/2)\ v\,(t)^3 \tag{1}$$

- *Pw*: Output power of the wind turbine. Unit: Watts (W).
- *Cp(λ,β)*: Power coefficient, which depends on the tip speed ratio (λ) and blade pitch angle (β). This coefficient represents the efficiency of the wind turbine in converting the kinetic energy of the wind into mechanical power. It is a dimensionless quantity.
- ρ: Air density. Unit: kilograms per cubic meter (kg/m^3).
- *A*: Swept area of the turbine rotor. This represents the area swept by the turbine blades as they rotate. Unit: square meters (m^2).
- *v(t)*: Wind speed. This is the speed of the wind at a given time. Unit: meters per second (m/s).

We consider that P_n is the nominal power for the wind turbine, so $P_n = P_m\ (V_n)$ so Equation (2):

$$Pw = P_n\ v(t)^3 / \ Vn^3 \tag{2}$$

With $Vn = 10m/s$

We can express the relation that shows output power for the solar panel as follow Equation (3):

$$P_{pv} = P_r\ .Floss.\,(Gh\,(t)\ /Gs) \tag{3}$$

With $Gs = 1000\ W/m^2$

So $Pproduced = Ppv +\ Pwind$

The Figure 5 shows the produced power of renewable energy from different dispositives.

3.2 | Load Power

The power (P) of an electrical load is expressed using the formula Equation (4):

$$PL = V * I \tag{4}$$

Where:

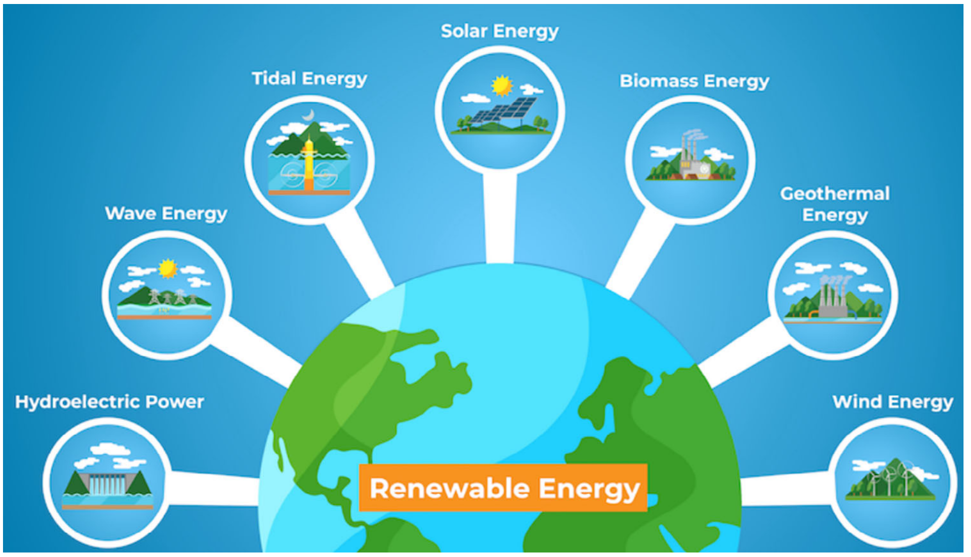

FIGURE 5 | The diversified renewable energy diapositives.

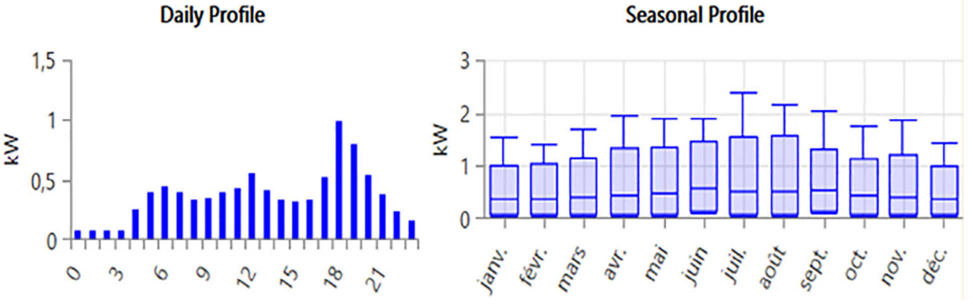

FIGURE 6 | The load power of one house.

PL is the power (measured in watts),
V is the voltage across the load (measured in volts),
I is the current flowing through the load (measured in amperes).

This formula is based on Ohm's Law, which states that the current flowing through a conductor between two points is directly proportional to the voltage across the two points, given a constant resistance.

The maximum current that can be drawn by a house for most of the circuits is up to 36 A with a high voltage supply of 220 V; then, using the Pmax = V·I formula, the theoretical power that can be consumed in the house will be 7.92 KW. This would mean the maximum power that the electrical system of the house can allow. In practice, peak load, meaning the maximum power the house draws at any one time, is roughly 2.5 KW, which is a far cry from the more theoretically derived maximum. This thus rather serves to illustrate that, in reality, the house operates well below its capacity. This discrepancy is normal since it considers the fact that not all home appliances and devices are running at the same time with their maximum rated power. This safety margin prevents the electrical system from overloading for stability and efficiency in variable power demands. The demand for one house with details and justifications is shown in the Table 1 and Figure 6: [1, 3, 11]:

The chart below displays the daily power consumption of a house on an hourly and a monthly basis:

3.3 | Stocked Power in the Batteries

The behaviour of a battery during charging and discharging can be described by the output power equation:

$$P(t) = V_{nominal} \cdot (1 - SOC(t)/Q) \cdot I(t) \tag{5}$$

When charging, the state of charge (SOC) increases as the battery accumulates energy, leading to a positive current flow into the battery. The voltage rises during charging, approaching the nominal voltage $V_{nominal}$ as the battery reaches full charge. The output power (P) is negative during charging, with its magnitude diminishing as the battery approaches full capacity. In the discharging phase, SOC decreases as energy is released, resulting in a negative current flow out of the battery. The voltage decreases during discharging, approaching the nominal voltage as the battery discharges. P is positive during discharging, with its magnitude decreasing as the battery

TABLE 1 | The estimated demand for electricity.

	Load type	Number	Power (Watts)	Summer	(May-Sep)	Winter	(Oct-April)
				Hrs/day	Watt-hrs/day	Hrs/day	Watt-hrs/day
Domestic Load							
1	CFL	4	22	10	880	7	620
2	CFL	1	12	8	96	11	132
3	Ceiling fan	1	121	20	2440	0	0
4	Kitchen fan	1	29	6	174	0	0
5	Cooler	2	121	10.5	2500	0	0
6	TV	1	99	9	890	6	591
7	PC	1	299	8	2392	9	2690
8	Exhaust fan	1	16	5	80	3	48
9	Table fan	1	16	8	124	0	0
10	Room heater	1	92	0	0	12	1104
11	Room heater	1	148	0	0	7	1036
12	Electric blanket	1	125	0	0	3	375
13	Vacuum cleaner	1	215	2	430	1	215
14	Bulb	1	102	1	102	2	204
	Total (one house)				10,143		6976
		1	1.4kw				

discharges. These dynamics highlight the interplay between voltage, current, SOC, and output power in governing the energy transfer processes within a battery during its operational cycles [15–17].

So we can also have, in order to express $P_b\ (t)$ in function of load, wind and P_v power, this Equation 6:

$$P_b\,(t) = P_L - P_{pv} - P_w \tag{6}$$

$P_b(t)<0$ means that $P_{pv}+P_w>P_L$ so energy is produced more than load demand, and there is an excess of energy to charge the battery. So this justifies why Pb is negative during charging.

In an analogue manner, $P_b(t)>0$ means that $P_{pv}+P_w<P_L$ so renewable resources are not enough, and we need energy from the batteries that is the discharge, and it justifies why Pb is positive during discharge [19].

3.4 | Biomass Gasifier

The power output (P) of a biomass gasifier can be expressed in terms of the gas flow rate (Q) and the heating value of the produced syngas (HV) using the following equation 7:

$$P = Q \cdot HV \tag{7}$$

Where:

P is the power output (measured in watts or kilowatts),
Q is the gas flow rate (measured in cubic meters per second or other appropriate units),
HV is the heating value of the syngas (measured in joules per cubic meter or other appropriate energy units).

3.5 | The Dump Load

The dump load equation, denoted as (Equation 8):

$$P = V^2/R \tag{8}$$

It represents a mathematical relationship crucial for determining the power dissipation required by a dump load in renewable energy systems. Specifically designed for safeguarding electrical systems from potential overvoltage or overcurrent scenarios, dump loads are commonly implemented in setups featuring wind turbines or solar panels.

Breaking down the equation:

- P: This signifies the power that needs to be dissipated by the dump load.
- V: Represents the voltage in the system.
- R: Denotes the resistance of the dump load.

The equation shows power dissipation demand P is directly proportional to the square of the voltage, V^2, and inversely proportional to the resistance R. In other words, for the dump load, an increase in voltage or a drop in resistance automatically means increased demand for more power dissipation.

An adequate value of resistance must be chosen for real-life applications of the dump load: if the value of resistance is too low, too much current will pass through the dump load and will probably overheat or fail. On the other hand, if the resistance is too high, insufficient power dissipation may result in potential damage to the electrical system [19].

This equation underlines that the value of the resistance of the dump load has to be chosen with care with respect to the peculiar characteristics of the electrical system in order to make the right compromise between safety and functionality [20, 21].

3.6 | The Inverter

The inverter is a critical component within the microgrid, where renewable-generated DC electricity-solar panels or batteries, for example-is converted into AC electricity that is usable within homes, businesses, and the electrical grid. The primary purpose of an inverter is to invert the direction of the electric current.

Some inverters can perform bidirectional energy conversion, meaning they are able to convert DC to AC and vice-versa. These kinds of devices are popularly known as bidirectional or hybrid inverters. Because of their capability to convert power both ways, it is found suitable for applications requiring a bidirectional flow of energy with the grids for energy storage.

In particular, it is during the conversion of AC to DC that the inverter is normally in a mode called 'rectification', wherein it converts AC power into DC power. This functionality is oftentimes helpful in situations where energy has to be stored within batteries or when power has to be supplied to DC loads.

The relation of the input power (DC PDC) and the output power (AC PAC) of an inverter can be expressed by the following equation, considering the efficiency of the inverter η [22–24] Equation (9):

$$P_{AC} = \eta_{inv} \times P_{DC} \tag{9}$$

Or $PDC = \eta_{inv} \times P_{AC}$ for bidirectional inverters

Where:

P_{AC} is the alternating current (AC) power output.
P_{DC} is the direct current (DC) power input.
η is the efficiency of the inverter.

While taking into consideration the inverter and its efficiency the power of battery Pb will become:

$$Pb\,(t) = (Pw - PL)\,\eta_{inv} + Ppv \quad for \quad PL < Pw$$

$$Pb\,(t) = Ppv - (PL - Pw)\,/\eta_{inv} \quad for \quad Pw < PL < Pw + Ppv$$

$$Pb\,(t) = (PL - Pw)\,\eta_{inv} - Ppv \; else$$

4 | Dynamic Management of Energy Contribution and the Role of AI and IOT to Improve it

4.1 | Dynamic Energy Management (DEM)

DEM in microgrids is one such intelligent approach toward real-time optimisation in the distribution and consumption of energy resources by dynamically responding to changes in conditions and demand. This contrasts with static energy management techniques, which rely on predetermined and unchanging sets of strategies. DEM employs real-time data, forecasting, and adaptive algorithms to achieve a far more efficient and resilient microgrid than either of the other two approaches in isolation could do [22, 23].

The most important advantage of DEM is the dynamic balancing of supply and demand through predictive analytics and adaptive control strategies. DEM takes into account variable factors that include renewable energy generation variability, load variations, and shifting environmental conditions. DEM's optimisation objective is to continuously monitor the operation, apply corrective actions, and thus work out an optimal energy distribution that matches the current and forecasted demand of all components of microgrids, including renewable energy sources, energy storage systems, and demand-side devices, in consideration of system constraints.

One of the most valuable features of DEM is its ability to deeply integrate renewable energy sources such as solar and wind into the microgrid. Dynamic management allows for real-time adaptation to the intermittency and variability of these renewable sources, enabling high utilisation without sacrificing microgrid stability. Besides, DEM enables the smooth integration of energy storage systems like batteries by smartly managing the charge and discharge cycles in accordance with the prevailing energy generation and demand conditions. Moreover, DEM enhances the resilience and reliability of the microgrid, as it operates within the shortest period of time in response to unexpected contingencies that come in the form of sudden changes in load or even equipment failures. The adaptive nature of dynamic management consists in that a microgrid will change its approach to energy distribution without significant disruption immediately to maintain operation stability due to the unexpected disruption.

While energy management is generally approached from a static point of view that cannot catch up with the dynamics imposed by real-time variability, DEM represents a more sophisticated and responsive remedy.

This allows for the optimised energy flows within prevailing and forecasted conditions and has a cascading positive effect on energy efficiency, cost reduction, and increasing renewable shares. Overall, DEM is forward-looking and offers effective and flexible solutions for the energy system of the future, bounded by sustainability, reliability, and adaptability [24, 25].

4.2 | EMS Dynamic Algorithm to Manage Energy

The EMS has a central role in the dynamic process of interactions among multiple sources of energy within the microgrid. In the algorithmic operation of the system, renewable sources are prioritised through the integration of real-time data and weather forecasts. Meanwhile, batteries are used as vital storage units, the charging-discharging of which is tactfully intercepted by EMS algorithms in a manner that would achieve the highest effectiveness, prolonging the operating life. Biomass acts as a reliable backup against fluctuating renewable energy generation and sudden disturbances on the grid; its usage is optimised by EMS algorithms based on given parameters such as cost-effectiveness and environmental impact. It provides an intelligent layer of defence wherein the dump loads are employed judiciously. Thus, this load is utilised when the batteries are full and there is excess energy to be dissipated to harden the microgrid in case overloads occur. It ensures that all the parameters are kept within continuous and stable limits, thereby acting according to the adaptive and resiliency features of the microgrid since it changes from one state of operation into another [4, 11, 12].

This basically means that any EMS's key role is to make optimal-informed decisions in real-time, and it is very critical since energy systems are inherently dynamic. The two key variables that form the very basis of it all, wind speed and solar irradiance, have a volatile nature and can never be completely predicted with complete accuracy. These resources, however, remain very valuable forms of renewables in view of this volatility: they are free and carbon dioxide emission-free. The challenge for the EMS is to exploit and capture this intermittence. Through the use of advanced algorithms and predictive analytics, the EMS tries to anticipate and adjust to varying wind speed and solar irradiance as a means of optimising the usage of these clean energies. In essence, the key challenge is achieving an adequate balance between the intermittency of the one and the necessity of using them appropriately for a sustainable generation of energy in the microgrid with a limited environmental impact.

The dynamic algorithm can be explained by the organigram in Figure 7:

This algorithm forms the central feature of our EMS, and its explanation in detail is vital for optimisation. For the major inputs of the algorithm, it was extended in Section 3 that they are the power generated by wind turbine Pw, the generated power of the solar panel Ppv, and the load demand (PL). Before any decisions, the algorithm needs the SOC of the battery, hereafter denoted as SOC(t), compared with the minimum and maximum thresholds for SOC. Then, the algorithm will decide to start the charging or discharging of the battery, biomass utilisation, or stop it, and whether energy should be dumped through the dump load. Also, when all these will stop. These decision-making processes are involved in an extremely complicated way; hence, to understand them, the effective working and optimisation of our EMS become very vital [17, 26].

4.3 | IoT and AI Contribution to EMS

The integration of AI and IoT in EMS brought huge changes in microgrids, ensuring efficiency, reliability, and sustainability. AI might be crucial in a microgrid, normally developed as a smaller local and sometimes decentralised energy system, for predictive analytics, load forecasting, and optimisation in energy use. The AI framework can, therefore, make use of machine learning algorithms in analysing historical data to predict future energy demands and create proactive decisions for energy distribution. The IoT does handle this quite nicely since it creates an interlink of devices that, in real-time, transfer information on the efficiency of the operation of a microgrid. In this context, data on energy generation and usage, or grid conditions, are continuously monitored and captured from smart meters, sensors, and actuators spread across the microgrid. Thus, AI and IoT together provide synergistic effects with dynamic adjustments to meet the varying conditions so that a microgrid's performance can be optimised to ensure reliability of supply. In addition, predictive maintenance by AI will have early detection of possible major faults, thus reducing downtime and facilitating cost reductions. Therefore, in an integrated AI-IoT-powered EMS of a microgrid, the power would add a resilient, sustainable, and smart element to the energy infrastructure for which the world is thinking today [27, 28]. Taken together, the IoT and AI will make a microgrid immune to much energy waste and cost because of its ability to intelligently manage power flow. In the following examples, although hypothetical, the integration could thus bring tangible benefits in Table 2:

5 | Stimulation on an Example of an Islanded Microgrid With a Load of 100 Houses and Interpretation of Results With Future Perspectives

The optimisation problem for the EMS was formulated to minimise energy wastage and operational costs while maintaining system reliability. The objective function is defined as minimising the sum of energy losses, also known as dumped energy, and economic costs, subject to constraints such as energy balance, storage capacity limits, and system demand. The genetic algorithm was utilised to solve this problem efficiently, providing near-optimal solutions within a reasonable computational time.

The choice of a genetic algorithm (GA) for this study stems from its proven effectiveness in solving complex, non-linear, and multi-objective optimisation problems. Unlike traditional optimisation techniques that rely on gradient information or linear assumptions, GAs excel in exploring vast and complex solution spaces through iterative evolution. This makes them particularly suitable for energy management in microgrids, where variables such as energy demand, renewable generation, and storage dynamics exhibit high non-linearity and interdependence. Additionally, GAs offer robustness against local minima, ensuring a higher likelihood of finding globally optimal solutions, which is critical for achieving the dual objectives of minimising energy wastage and maintaining cost efficiency.

5.1 | The Main Characteristics of Our Microgrid Subject to the Simulation

Our microgrid is strategically designed to meet the electrical energy needs of a community comprising 100 houses, each with an estimated average load of 47 kW, fluctuating between 15 kW and 120 kW as shown in the Figure 8:

The nominal power of the solar panels is Pvn = 50 kW, while the wind energy system has a nominal power of Pwn = 50 kW.

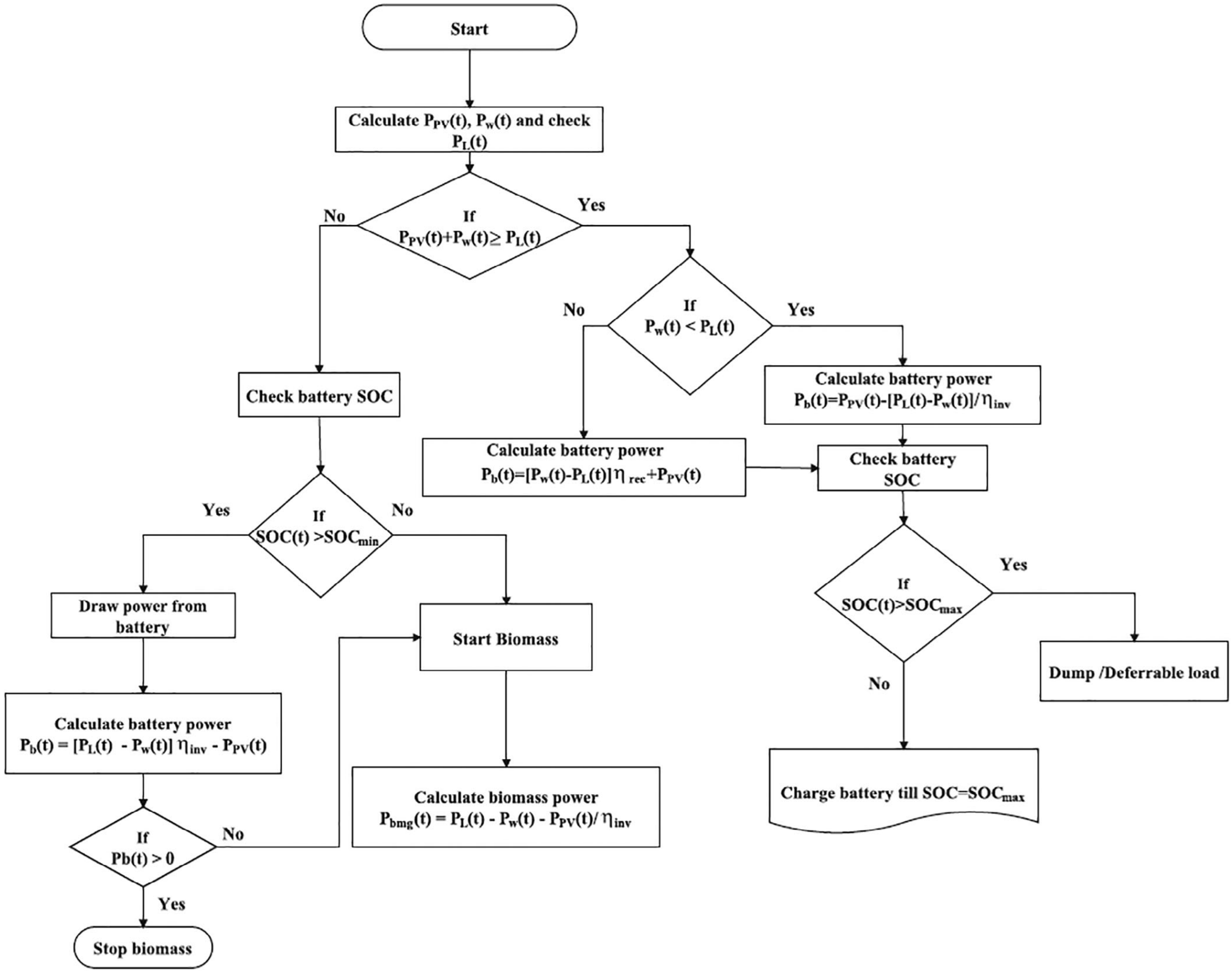

FIGURE 7 | Organigram of EMS algorithm.

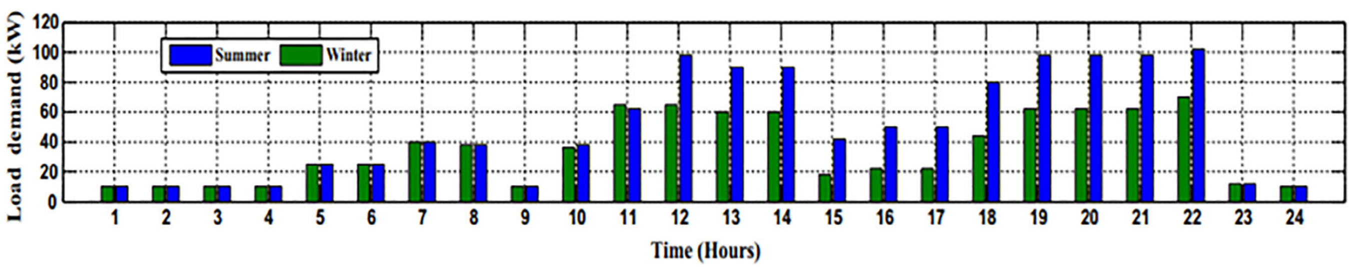

FIGURE 8 | The hourly load demand in summer and winter.

With regard to energy storage, batteries represent the supporting elements of the microgrid and have a remarkable power of 200 kW, which enables the entire system to gain about three months of autonomy.

It will employ a very strong 150 kW inverter, which will be converting energy into usable forms and efficiently distributing it within the microgrid. This inverter is important in ensuring a stable and reliable supply to the community.

Within the microgrid, the backup is a 50-kW biomass source from variable renewable energy generation and/or unexpected grid disturbances. In cases when either renewable sources alone or their support with batteries cannot provide the required energy needs for the community, this biomass source acts as a reliable supplement.

In brief, the integrated solar, wind, and biomass energy sources with advanced energy storage and distribution technologies

TABLE 2 | Some optimisation methods through AI and IoT and their hypothetical results.

Method	Scenario	Results
Demand/response optimisation	AI algorithms analyse historical data and real-time information from IoT devices to predict peak demand periods.	The system anticipates high demand, optimising the distribution of energy resources by dynamically adjusting power generation and storage. This reduces the need to activate costly backup generators during peak hours, resulting in about a 15% reduction in energy costs.
Predictive maintenance for equipment efficiency	IoT sensors continuously monitor the performance of equipment within the microgrid, providing real-time data to AI systems.	AI algorithms detect potential issues in equipment such as solar panels or batteries before they lead to inefficiencies. Proactive maintenance reduces downtime, increases equipment lifespan, and lowers maintenance costs, resulting in a 20% decrease in overall maintenance expenditures.
Load balancing and energy storage optimisation	AI algorithms, based on IoT data, analyse patterns of energy consumption and generation within the microgrid.	The system optimally balances loads, shifting energy consumption to times of lower demand and maximising the utilisation of energy storage systems. This leads to a 10% reduction in wasted energy, as excess energy is stored during periods of low demand and utilised during peak hours.
Grid resilience through predictive analytics	AI uses historical and real-time data from IoT devices to predict potential grid failures or disruptions.	The system takes proactive measures to reroute power and isolate affected areas, minimising the impact of disruptions. This results in a 25% reduction in downtime and associated costs.
Dynamic pricing and cost savings	AI analyses market conditions, energy demand, and production costs using IoT data.	The microgrid adjusts pricing dynamically, encouraging energy consumption during off-peak hours. Consumers benefit from lower prices during periods of low demand, leading to a 15% reduction in energy costs for end-users.

in the microgrid ensure that, even in a community with 100 diverse houses, the power supply is sustainable and resilient. In short, the all-inclusive system will aim to ensure seamless electricity supply while improving energy self-sufficiency and environmental sustainability.

In our study, we implement an EMS in dynamic mode, utilising simulation-based analysis to assess its performance. To evaluate the effectiveness of the EMS, we monitor dumped energy and produced energy on an hourly basis, defining the temporal granularity of our data acquisition. This granularity ensures a balanced trade-off between capturing meaningful system dynamics and maintaining computational efficiency. The analysis is conducted through simulations using Python and MATLAB, enabling precise modelling of energy flows and system behaviour under various conditions. By leveraging these computational tools, we demonstrate how the EMS dynamically adapts in real time, minimising energy waste and enhancing overall system efficiency.

5.2 | Real Results, Visualisation, and Explanation for both Microgrids With EMS and without EMS

We will transform the organigram, in addition to the main equations of our microgrid, into a Python program.

With irradiation Gs(t), wind speed V(t), and load demand PL as inputs our outputs, that we want to visualise will be (consumed power P(t) and dumped power in the dump load Pd(t)).

In the simulation, time was discretised into one-minute intervals as a balance between computational feasibility and operational accuracy. This granularity of time allows the system to capture the rapid fluctuations in energy demand and supply while maintaining the results within computationally feasible bounds. Sensitivity analysis showed that reducing the time step to smaller intervals, such as one second, provided negligible improvements in accuracy but significantly increased computational overhead.

We will simulate on, 24 h with a time step of 1 h.

The algorithm of our Python program with EMS is explained like this:

1. **Initialise microgrid parameters**:
   - Create a class (‘Microgrid‘) to encapsulate the microgrid parameters, including biomass, PV, wind, and battery capacities, as well as the load profile.
   - Include methods for calculating energy generation, charging/discharging batteries, activating dump loads, and visualising results.
2. **Run microgrid for each hour**:

- For each hour in the simulation (24 hours):
- Generate random inputs for wind speed, solar irradiance, and load demand.
- Call a method (‘run_microgrid‘) to simulate the microgrid operation for the current hour.
- Inside the ‘run_microgrid‘ method:
- Calculate energy generation from biomass, PV, and wind sources.
- Determine the total demand and charge/discharge the batteries accordingly.
- Calculate consumed energy and dumped energy.
- Visualise the results for the current hour (e.g., print or store the values).

3. Visualise Overall Results
   - After the 24-hour simulation:
   - Visualise the overall results, such as the consumed and dumped energy, using appropriate visualisation tools (e.g., plots).
   - This could involve creating lists or arrays to store the consumed and dumped energy values for each hour during the simulation.

The results of our program presented in the Table 3:

The sum of the power outputs for each hour divided by the number of hours in a day is the daily average power consumed

In our case average consumed power ACP = 69 KW

In an analogue manner, the average dumped power is ADP = 18.3 KW

In order to better understand and interpret these results, it is necessary to compare them to the scenario in which the microgrid operates at the maximum energy demand and does not have any EMS.

In this case the microgrid operates without an EMS, and for each of the 24 simulation hours, random inputs for wind speed, solar irradiance, and load demand are generated. The microgrid calculates the total energy generation from biomass, PV, and wind sources, charges/discharges the batteries based on available renewable energy, and determines the consumed and dumped energy. The results for each hour are then visualised [29–31].

The algorithm for the microgrid without EMS is

1. **Initialisation**:

Initialise microgrid parameters such as biomass capacity, PV capacity, wind capacity, battery capacity, and load profile.

Set the initial state of the battery to zero.

2. **Energy generation**:

For each simulation hour:

Generate random values for wind speed, solar irradiance, and load demand.

TABLE 3 | Consumed and dumped energy in a microgrid with EMS.

Hours of the day	Hourly consumed energy in KW	Hourly dumped energy in KW
Hour 1	40	60
Hour 2	80	20
Hour 3	30	70
Hour 4	60	0
Hour 5	50	50
Hour 6	70	0
Hour 7	90	0
Hour 8	70	0
Hour 9	100	0
Hour 10	80	20
Hour 11	110	0
Hour 12	60	0
Hour 13	70	0
Hour 14	80	20
Hour 15	40	60
Hour 16	90	0
Hour 17	80	0
Hour 18	30	70
Hour 19	50	50
Hour 20	60	0
Hour 21	70	0
Hour 22	80	20
Hour 23	90	0
Hour 24	60	0

Calculate energy generation from biomass, PV, and wind sources based on the generated values.

3. **Load demand adjustment**:

Determine the load demand for the current hour based on the generated load profile.

Adjust the demand to be within the range of 15 KW (minimum) and 120 KW (maximum).

4. **Battery charging and discharging**:

Calculate the available renewable energy by summing biomass, PV, and wind generation.

Determine excess energy by subtracting the demand from available renewable energy.

Charge the battery with excess energy, up to its capacity.

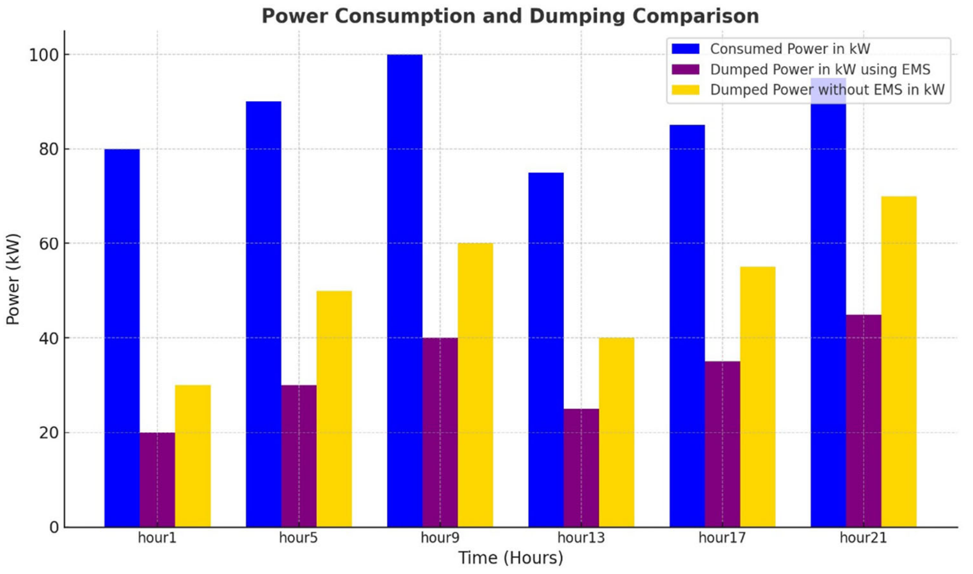

FIGURE 9 | The power flow in a microgrid.

If demand exceeds available renewable energy, discharge the battery to meet the demand, up to its remaining stored energy.

5. **Dump load activation**:

Activate dump loads to simulate the inefficiency without an EMS.

Dump loads receive excess energy, and the dumped energy is calculated as 1.5 times the excess energy.

6. **Results visualisation**:

Visualise the results for the current hour, including consumed energy and dumped energy.

7. **Repeat**:

Repeat the process for all 24 simulation hours.

Results Summary:

Display the overall results, including the consumed and dumped energy for each hour.

The new results will be in Table 4:

In this case without EMS average consumed power ACP = 69KW

The average dumped power is ADP = 27.5KW (Figure 9)

5.3 | Optimisation of Our EMS Algorithm Using AI and IoT With New Results

AI and IoT are to be used. In actual world implementation, this intelligent dynamic adjustment of the capacities of PV and wind would take into account weather conditions, advanced control systems, and sensor technologies in building up a microgrid.

TABLE 4 | Consumed and dumped power in an MG without EMS.

Hours of the day	Hourly consumed energy in KW	Hourly dumped energy in KW
Hour 1	40	80
Hour 2	80	40
Hour 3	30	100
Hour 4	60	0
Hour 5	50	75
Hour 6	70	0
Hour 7	90	0
Hour 8	70	0
Hour 9	100	0
Hour 10	80	30
Hour 11	110	0
Hour 12	60	0
Hour 13	70	0
Hour 14	80	30
Hour 15	40	90
Hour 16	90	0
Hour 17	80	0
Hour 18	30	105
Hour 19	50	75
Hour 20	60	0
Hour 21	70	0
Hour 22	80	30
Hour 23	90	0
Hour 24	60	0

Automated control capitalises on weather forecasting data and ML algorithms to forecast changes and automatically increase capacities in favourable scenarios such as high solar irradiance or strong winds. These include solar irradiance sensors and anemometers that provide real-time data to inform capacity adjustments. Smart grid technologies and bidirectional communication with utilities enable the microgrid to adapt based on grid conditions and demands. Remote monitoring systems allow for centralised control, and manual intervention by operators may be facilitated. It includes incentives for regulatory uses of renewable energy sources when conditions are favourable and economic considerations, such as cost-benefit analyses. Moreover, storage systems, such as batteries, provide the possibility of saving surplus energy produced at optimal conditions for later use when needed, hence increasing efficiency and reliability in the microgrid. However, such advanced strategies will be implemented in cooperation with experts in renewable energy and control systems to achieve an effective and sustainable resolution [31–33].

IoT technologies are thus the basic building blocks for EMS because of their capabilities to perform real-time monitoring and controlling of energy resources. Embedding sensors and devices within an IoT provides continuous data collection with respect to energy production, consumption, and storage levels, which gets transferred to the central AI for processing and analysis. With the capability for IoT components to talk perfectly among themselves, for example, the EMS will dynamically react to any change in condition, such as peak demand or an unexpected drop in generation. That will not only secure operational efficiency but support predictive maintenance with the identification of system failures even before their occurrence [34, 35].

For this the EMS integrates various IoT devices to enable real-time monitoring and control of the microgrid. These devices include smart meters, which track energy consumption at individual households; sensors for monitoring renewable energy generation (e.g., solar irradiance sensors and wind speed sensors); and battery management systems that report storage levels and performance. Communication modules, such as Zigbee or LoRa, connect these IoT devices to the central EMS, ensuring seamless data flow. This integration allows the EMS to collect, analyse, and act upon real-time data, optimising energy distribution and storage decisions dynamically. The use of IoT technology enhances the microgrid's responsiveness, efficiency, and overall reliability [36, 37].

In this extended programme, a new class called 'Microgrid Controller' is added for IoT and AI-based optimisation of the operation of the microgrid. This would be done to enhance the performance of the microgrid dynamically based on incoming real-time data and with the use of an AI optimisation algorithm. The main methods in the 'Microgrid Controller' class are 'optimise_microgrid' and 'run_optimised_microgrid' [38].

1. **'optimise_microgrid' method**:
   - This method is responsible for adjusting the microgrid parameters based on the current environmental conditions, such as wind speed, solar irradiance, and load demand.
   - In the provided example, a rule-based optimisation strategy is implemented for simplicity. It adjusts the PV and wind capacities based on certain conditions: increasing them during favourable conditions (high wind speed and solar irradiance) and reducing them during less favourable conditions.
2. **'run_optimised_microgrid' method**:
   - This method serves as the entry point for running the microgrid with the optimised parameters.
   - It first calls the 'optimise_microgrid' method to dynamically adjust the microgrid parameters based on real-time data.
   - Then, it calls the 'run_microgrid' method of the original 'Microgrid' class to simulate the microgrid operation with the adjusted capacities.
   - The resulting consumed energy and dumped energy values are returned, representing the performance of the microgrid under the dynamically optimised conditions.

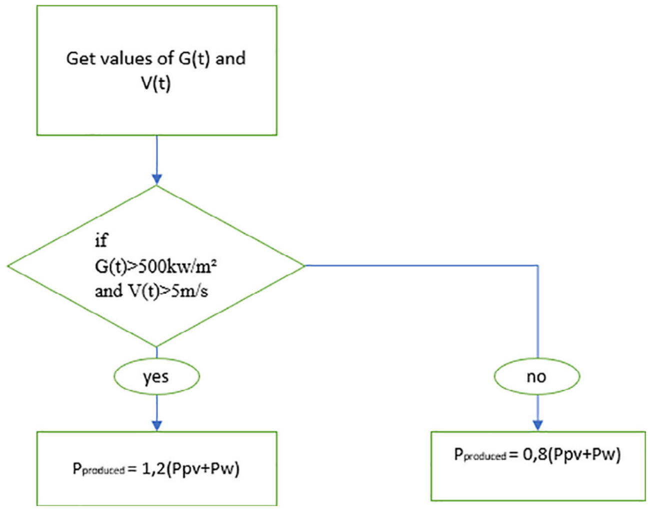

FIGURE 10 | The optimised microgrid organigram.

In a nutshell, the class Microgrid Controller mediates between the external environment and the microgrid system. It applies an optimisation algorithm to this work; a rule-based strategy has been used for simplicity that changes the microgrid capacities according to the variations that take place with the objective of finding the best improvement in efficiency or global performance of the system. A controller of this type can integrate and allow the microgrid to operate in a more adaptive and intelligent manner, making real-time data available for AI-driven decision-making to optimally utilise the renewable energy sources, as presented in the following Figure 10:

The results of the visualisation of the dumped power of the microgrid using an extended version with IOT and AI are detailed in the Table 5:

The average dumped power is ADP = 1.8KW (Figure 11).

The AI integration within the EMS has been done to control the energy resources of the microgrid effectively using advanced optimisation techniques. Specifically, an optimal energy storage and distribution schedule was obtained using GA. Genetic algorithms are also very suitable for this task because they can

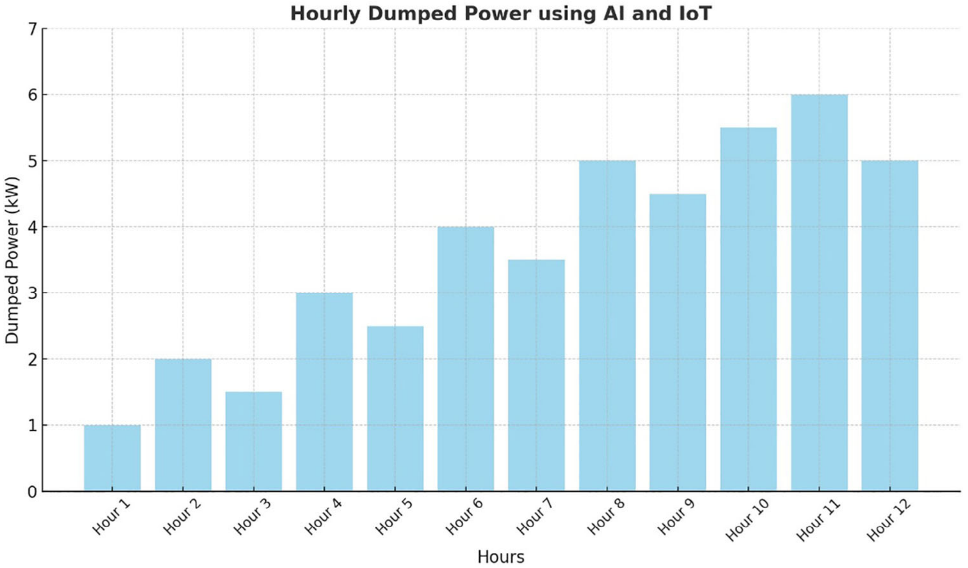

FIGURE 11 | Hourly dumped power using AI and IoT.

TABLE 5 | Consumed and dumped power in an MG with EMS enhanced with IOT and AI.

Hours of the day	Hourly consumed energy in KW	Hourly dumped energy in KW
Hour 1	40	0
Hour 2	80	2
Hour 3	30	0
Hour 4	60	5
Hour 5	50	0
Hour 6	70	3
Hour 7	90	0
Hour 8	70	4
Hour 9	100	1
Hour 10	80	0
Hour 11	110	6
Hour 12	60	1
Hour 13	70	2
Hour 14	80	0
Hour 15	40	3
Hour 16	90	0
Hour 17	80	6
Hour 18	30	1
Hour 19	50	0
Hour 20	60	5
Hour 21	70	1
Hour 22	80	2
Hour 23	90	0
Hour 24	60	3

handle nonlinear and multi-objective optimisation problems. The algorithm iteratively improves the solutions through artificial intelligence based on natural selection for an efficient exploration in solution space, with very slight energy losses and the best possible cost-balancing.

5.4 | Discussion of Results and Future Perspectives

This paper, with regard to the energy management of a microgrid, considers three scenarios: a simple microgrid, a microgrid that is enhanced with an EMS, and an advanced microgrid that will include EMS, artificial intelligence, and the Internet of Things. In the simple microgrid, the energy that is not utilised by the loads or stored in the batteries is dumped into a dump load, implying a loss of energy and finances. Adding an EMS to the system optimises energy distribution, hence minimising the energy losses as opposed to a basic microgrid. AI and IoT integrated into the most advanced microgrid bring dynamic adaptiveness due to changeable conditions, real-time decision-making, and sophisticated energy predictions, which in turn bring minimal loss of energy and huge savings in cost. The progressive movement from a simple microgrid to one with EMS, AI, and IoT underlines the possibility of going for a more efficient and economically viable EMS [4, 6, 17]. Figure 12 below shows the variation of the most electrical parameters of a house.

The previous results show that for a microgrid used to give power to 100 houses (average 47kw load)

ADP = 27,5 KW for the normal microgrid without EMS
ADP = 18.3 KW for a microgrid with EMS
ADP = 1.8 KW for a microgrid with EMS, AI and IoT

In that perspective, the addition of no more than EMS itself can reduce energy losses by 35%, while the addition of AI and IOT

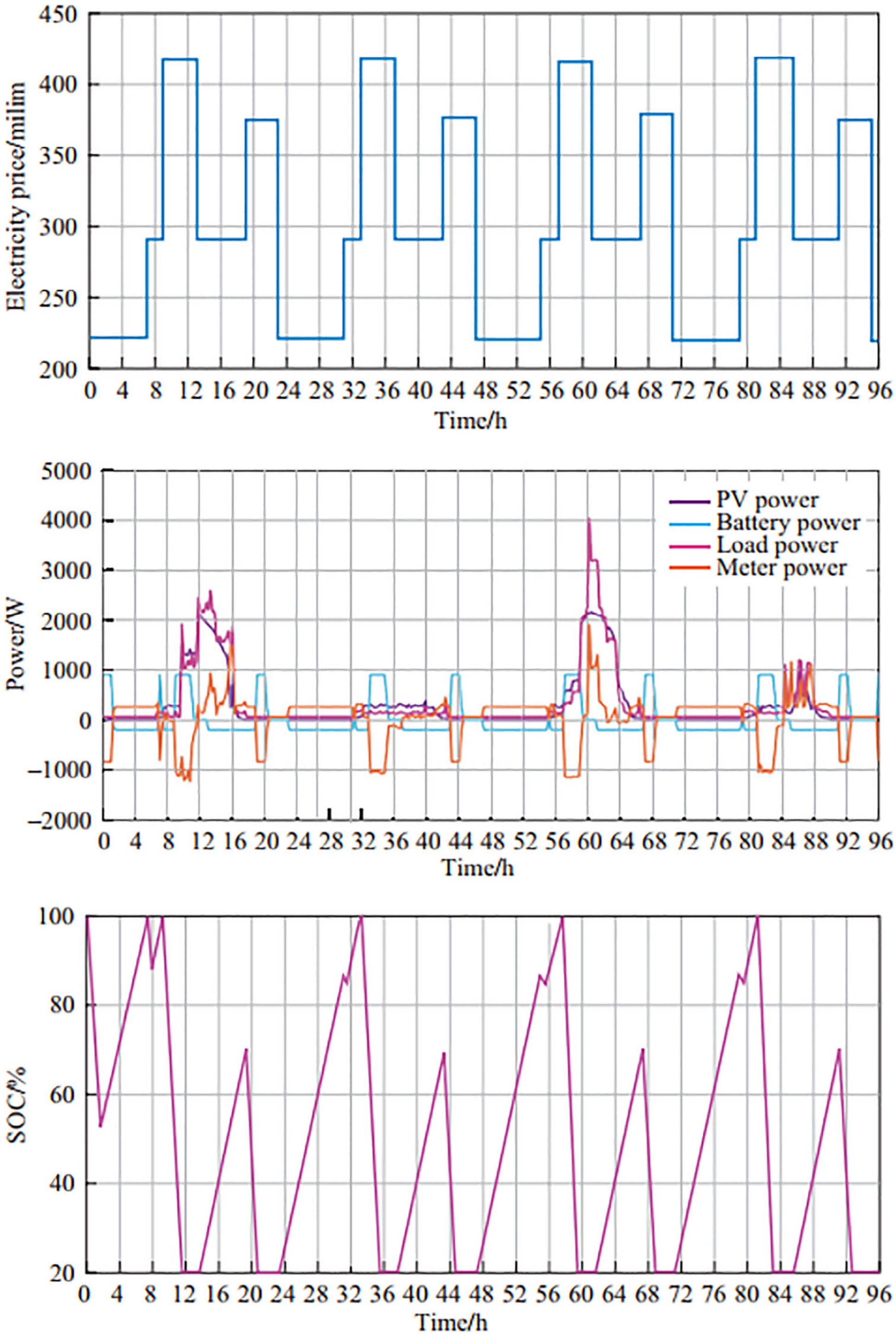

FIGURE 12 | The variation of power and price in 4 days.

for prioritising renewable energies when the climate is favourable and reducing them when it is not can reduce energy losses as high as up to 93%. In such context, considering that the amount of energy lost in an average case without EMS accounts for 27.5 KW out of 69 KW of energy stored and consumed, losses would account for 28% of the total amount of energy produced, while the usage of EMS would account for just 20% of the total losses of the microgrid; therefore, an 8% reduction in the total cost of the microgrid will be achieved. On the other hand, adding AI and IOT into the EMS will further reduce losses to 2.5% of the total energy produced, reducing in general the cost by 25% on the microgrid.

The chart below shows the used and dumped power in the three cases (Figure 13).

Future possibilities and avenues for refinement could look very exciting, as huge strides in microgrid power flow management will be possible with the integration of EMS, AI, and IoT.

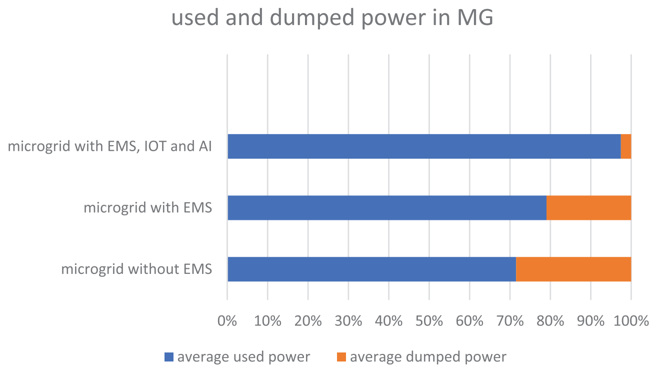

FIGURE 13 | Visualisation of the comparison of the energy results.

Avenues for cost reduction in implementing and maintaining EMS could be explored as researchers go deeper into the potential of advanced technologies, thereby fostering wider accessibility and adoption. This is a rich field for innovation in cybersecurity concerns and calls for the need to develop robust systems that resist such threats as they continue to evolve. The challenge of reduced battery life creates more opportunities for breakthroughs in battery technology by encouraging the development of means of energy storage that are much more durable and resilient. Interdisciplinary collaboration in energy engineering, cybersecurity, and materials science can act as a catalyst for developing holistic solutions working around these constraints. Further studies in the analysis could, therefore, be carried out on the socio-economic impact brought about by the widely implemented EMS on whether it could be employed to empower local communities and thus contributing to sustainable development. The present findings, while adopting a forward-looking approach, stand as testimony to not only the transformative potentials of EMS integrated with AI and IoT for microgrid management but also have inspired a roadmap for continuous innovation and advancement in the dynamic landscape of energy technology [31, 32].

In order to validate the performance of the proposed approach, a comparison analysis was conducted using the IEEE 13-node test feeder, which is a well-accepted benchmark system in microgrid research. The results showed that our integrated IoT and AI-enabled EMS achieved a 93% reduction in waste power, compared to the benchmark system, which achieved a waste power reduction of 88% under similar conditions. However, the cost increase in the proposed system was 25% while that for the benchmark was 20%, which highlighted the trade-off between increased efficiency and economic viability.

Whereas these results depict a total wasted power reduction of up to 93%, there is also an increase in total cost by about 25%. This kind of trade-off does confirm that there are some economic obstacles to the implementation of advanced EMS systems in microgrids. Detailed cost-benefit analysis manifests that most of these extra costs come from the highly invested capital in IoT and AI infrastructure and maintenance of the sophisticated hardware components. These costs are partly offset by long-term savings due to increased system efficiency and reduced reliance on non-renewable energy sources. Policymakers and stakeholders have to make trade-offs in these directions with a view to sustainability in implementation.

6 | Conclusion

Diving deeper into exploring ways of achieving better management in energy flow, our study depicts a tale of technological advancement with the integration of the extended version of the advanced EMS, IoT, and AI. With detailed unloading of EMS intricacies and elaboration on microgrid components, a sound backbone was formed for subsequent simulation, executed using Python so aptly emulating this realistic scenario: powering 100 households in a microgrid environment averaging 47 kW. These simulated results constitute the empirical backbone and show a staggering 93% reduction in wasted power when moving from a microgrid without EMS to one with enhanced energy management. This important enhancement underlines not only the technical dimensions of our study but also rhymes with practical implications. We further show a significant 25% reduction in overall microgrid costs, corroborating theoretical benefits and placing our integrated approach as a tangible, economically viable solution.

However, our research does not bask in the glory of successes but rather looks critically at the challenges that also come with it. We point at different economic problems as to the implementation cost of the EMS and further upkeep costs, situating the discussion in the realm of practical reality for its actual implementation. Furthermore, we emphasise hard cybersecurity measures with a view to safeguarding this interconnected microgrid against possible threats by realising its natural vulnerabilities in cyberspace.

Additionally, our study has also identified the possibility of reduced battery lifespan due to the optimised charge and discharge cycles emerging out of the EMS. These would, in turn, be a very interesting area for future studies and thus bring awareness toward the long-term viability of microgrid infrastructures in pursuit of innovative leaps toward better battery technologies.

By the time our study concludes with flair, it serves to open up a much greater dialogue rather than a purely technical discussion. This opens up interest not only within scientific circles but also among policymakers, economists, and environmentalists. It's more of a call for further exploration, collaboration, and innovation rather than a snapshot of what has transpired.

That is, our work represents the next phase in evolving sustainable energy solutions wherein improvements in EMS, IoT, and AI form integral parts of a look-ahead and holistic approach to EMS. Let us invoke all researchers and stakeholders to press forward to move towards a more efficient, resilient, and sustainable future energy scenario.

Future research could focus on addressing cost challenges associated with the implementation of such advanced EMS. Cost-reduction strategies will have to be explored through optimisation techniques and economies of scale. Integrating renewable energy forecasting and employing machine learning algorithms for predictive maintenance and fault detection could further operationalise efficiency and reduce downtime. Further studies on cybersecurity enhancement and regulatory frameworks are necessary to make interconnected microgrids robust. These directions will enable smart EMS to play a pivotal role in shaping resilient, sustainable, and economically viable energy systems.

NOMENCLATURE

AI	Artificial Intelligence
DEM	Dynamic Energy Management
EMS	Energy Management System
IOT	Internet of Things
SOC	State of Charge
V(t)	Wind speed in an instant t expressed in (m/s)
Gh(t)	Solar irradiance at an instant t expressed in (kw/m^2)
Pw	Wind turbine output power in kw
Ppv	Solar panel output power in kw
PL	Load power in kw
Pb	The batteries Power
ACP	Average Consumed Power expressed in kw
ADP	Average dumped power in the dump load expressed in kw
ηinv	Inverter efficiency

Author Contributions

Mohammed Amine Hoummadi: conceptualisation, data curation, format analysis, writing – original draft. **Badre Bossoufi:** conceptualisation, supervision, visualisation, writing – review and editing. **Mohammed Karim:** supervision, methodology, project administration. **Mohammed Hatatah:** validation, methodology, writing – review and editing. **Thamer A. H. Alghamdi:** format analysis, funding acquisition, methodology, investigation. **Mohammed Alenezi:** data curation, format analysis, funding acquisition, writing – review and editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data available on request from the authors.

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