Journal of Energy in Southern Africa

Volume 36 Number 1 2025

Analysis and mitigation of greenhouse gases by replacing traditional energy with a hybrid energy system using battery optimisation

Madhusudhanan Sampath[1], **Amalorpava Mary Rajee Samuel**[*2], **Yamuna Devi M M**[3], **Senthil Murugan**[4]

1 Department of Computer Science Engineering, Rajalakshmi Engineering College, Chennai, India

2 Department of Electrical and Information Engineering, University of the Witwatersrand, Johannesburg, South Africa

3 Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vijayawada, AP, India

4 Department of Computer Science and Engineering, Vel Tech High Tech Dr Rangarajan Dr Sakunthala Engineering College, Chennai, India

Abstract

Greenhouse gases (GHGs) are the main cause of global warming. Reducing emissions would contribute to environmental sustainability and could also have economic advantages. GHGs can be reduced by using the hybrid energy system (HES). In developing countries, analysing energy transitions and unmet energy needs should focus on identifying strategies for transitioning to more sustainable energy systems while ensuring access for all. This study looks at the mitigation of GHG emissions by using clean HES energy with battery optimisation. The paper presents an improved Lyapunov optimisation (LO) algorithm to optimally estimate the number of photovoltaic panels and battery banks for enhanced energy management. To increase system efficiency, the losses of power and over-production and under-utilised energy have been considered. The stability analysis is evaluated using the LO algorithm, specifically focusing on the changes predicted by the energy index of the self-reliance report, optimising the system's performance under varying environmental conditions.

Keywords: *hybrid energy system, Lyapunov optimisation, photovoltaics, energy index of self-reliance*

Journal of Energy in Southern Africa 36(1),1–12

DOI: https://dx.doi.org/10.17159/2413-3051/2025/v36i1a20374

Published by the University of Cape Town ISSN: 2413-3051 https://journals.assaf.org.za/jesa

Sponsored by the Department of Science and Innovation

Corresponding author: Email: maryrajee@gmail.com, maryrajee.samuel@wits.ac.za

1. Introduction

High levels of greenhouse gas (GHG) emissions, now concentrated at five times those seen before industrialisation (Verma et al., 2021), have had numerous impacts worldwide, such as heightened susceptibility of crops to diseases and pests, extreme weather and desertification. GHGs can absorb and release heat and ozone's hazardous gases. It is expected that global average surface temperatures will increase by 3.7°C by the 2070s, along with the 0.6°C global warming. This warming is likely to lead to drastic environmental changes in weather patterns and natural disasters (Thanh-Tuan Nguyan et al., 2021). An international agreement has been reached to prevent severe impacts from climate change by using the 2°C setting instead of the pre-industrialisation levels.

These difficulties require a reassessment of current mathematical methodologies (Ates et al., 2023; Jyoti et al., 2018; Balasubramaniam et al., 2025; He et al., 2023; Xu et al., 2020). A new and affordable power supply system is suggested to guarantee the use of clean electricity, with a particular emphasis on creating a pleasant atmosphere in a space. In addition, Tripp et al., 2022, proposed an energy management plan to enhance the energy efficiency of hybrid renewable energy systems (HESs) using stored unmet energy (Patel et al., 2019, Rajee et al., 2023). The reduction of CO_2 emissions requires increasing the efficiency of PV cells and battery storage optimisation (Rui Yang et al., 2021). So, clean energy transitions and energy-efficient HES are essential in reducing GHG emissions. To meet the 2°C upper limit, global annual CO_2 emissions of 5.2 tons per capita must be decreased to avoid the formation of acid rain. While CO_2 forms a mild acid when interacting with water, unlike sulphur and nitrogen oxides, which create strong acids, the rise in CO_2 emissions will worsen the issue. Marine scientists have shown great concern about the effect on sea animals. Changes in a species or a group of species caused by acidification will undoubtedly harm the ecosystem, particularly in terms of food. Abd, 2020, presented net-zero energy buildings as a promising strategy for decarbonisation, as they reduce energy consumption using grid-connected systems. The annual operating cost is too expensive, however (Kumar et al., 2022). Al-Rawashdeh et al. (2023 presented a study and assessed the impact of economic growth and fossil fuel usage. However, the current levelised cost of electricity from HES components is high for various reasons. The potential contribution and integration of HES systems depend strongly on local conditions. Battery storage systems can bridge the gap between variable and unsynchronised power supply and load demand (Ahmed et al., 2021).

1.1 Key contributors

Nitrous oxides, a significant source of GHGs, are primarily generated by microbial activity, and can also be attributed to the widespread use of nitrogen-rich chemical fertilisers. Carbon dioxide, the second biggest factor in the greenhouse effect, is generated naturally through volcanic eruptions and respiration, as well as through human activities and the burning of gasoline and other fossil fuels (Energy data info, 2023). Figure 1 shows the sectors mainly responsible for CO_2 emissions, and Table 1 shows the 10 countries contributing most to those emissions.

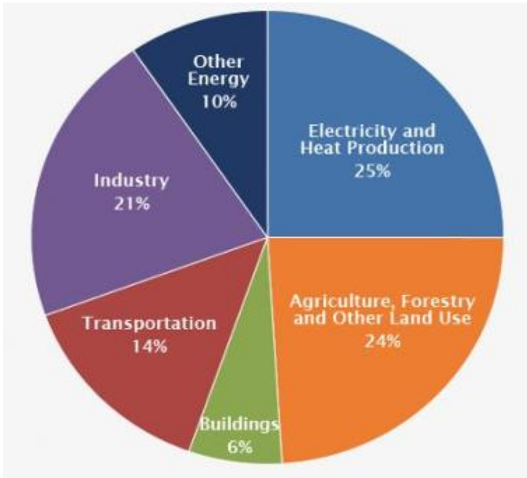

Figure 1: Global greenhouse gas emissions by sector (IPCC 2024)

Table 1: Top 10 carbon-emitting countries (IPCC 2023; IEA 2023)

Countries	*Million tons CO_2*	*Percentage of world CO_2 emissions*
China	13 300	32.38
USA	4 680	11.6
India	2 960	7.29
Russia	2 070	4.99
Japan	1 083	2.81
Indonesia	779	1.9
Iran	675	1.78
Germany	623	1.75
Saudi Arabia	620	1.71
South Korea	600	1.53

Currently, there is a lack of precise measurements on the atmospheric concentration of carbon monoxide, as its high spatial mobility hinders accurate assessment. The scenario shifts significantly with chlorofluorocarbons (CFCs) in the picture. Because it lacks natural sources, its atmospheric levels have been rising since they were first measured in 1928. There have been worldwide attempts to halt its use, including scientific reports generated by the Intergovernmental Panel on Climate Change (IPCC 2023).

1.2 Mitigating CO_2 emissions

A report from the International Energy Agency (IEA) stated that solar power has the potential to produce 22% of the world's electricity by 2050. Solar energy offers a way to reduce carbon emissions by replacing more carbon-intensive heat and power sources. The reduction depends on the energy sources displaced, their carbon intensity and the energy used in solar system manufacturing and operation. Life-cycle analysis shows that concentrated solar power (CSP) systems deliver power with a carbon intensity of 20-50 g CO_2/kWh. When integrated into energy systems, CSP's consistent power output and thermal storage reduce the need for storage and flexible capacity, making it easier to incorporate other variable sources like photovoltaics into grids (Solar Farm India, 2021).

The primary objective is to decrease CO_2 emissions to keep them within safe levels, while the secondary aim is to explore its utilisation in critical industrial applications. Lowering carbon discharges and enhancing sustainable energy sources is the main solution.

The research contributions of this paper stem from looking at the gap between CO_2 emissions and energy management optimisation. The implementation of Lyapunov optimisation can dynamically adjust decisions (such as when to store or release energy from batteries) based on real-time observation, leading to minimum carbon emissions. The optimum HES-LO helps ensure system stability by controlling the energy stored in batteries, over-discharge or under-utilisation of available renewable energy.

2. Related work

The integration of artificial intelligence (AI) with renewable energy sources offers real-time monitoring, data analytics and demand response to provide predictive maintenance and cybersecurity (Mikalai et al., 2024). The nature-inspired optimisation is utilised in solving large-scale nonlinear optimisation problems; particle swarm optimisation utilises swarm intelligence to solve renewable optimisation problems. The simplicity and the scalability of nature-inspired algorithms solve heuristic algorithms. AI has emerged as a transformative approach in optimising the energy management and consumption of clean energy. Machine learning contributes to demand forecasting and prediction using ensemble algorithms with support vector machines, random forest, and gradient boosting (Vendoti et al., 2020).

The GHG mitigation model in Figure 2 prevents emissions using cost-effective electricity production. The development of intelligence-based smart grids is emerging in scheduling, power consumption and transmission. Reinforcement learning is utilised for real-time control and decision-making algorithms for energy dispatching and storage operations (Samuel et al.,2020). Component sizing

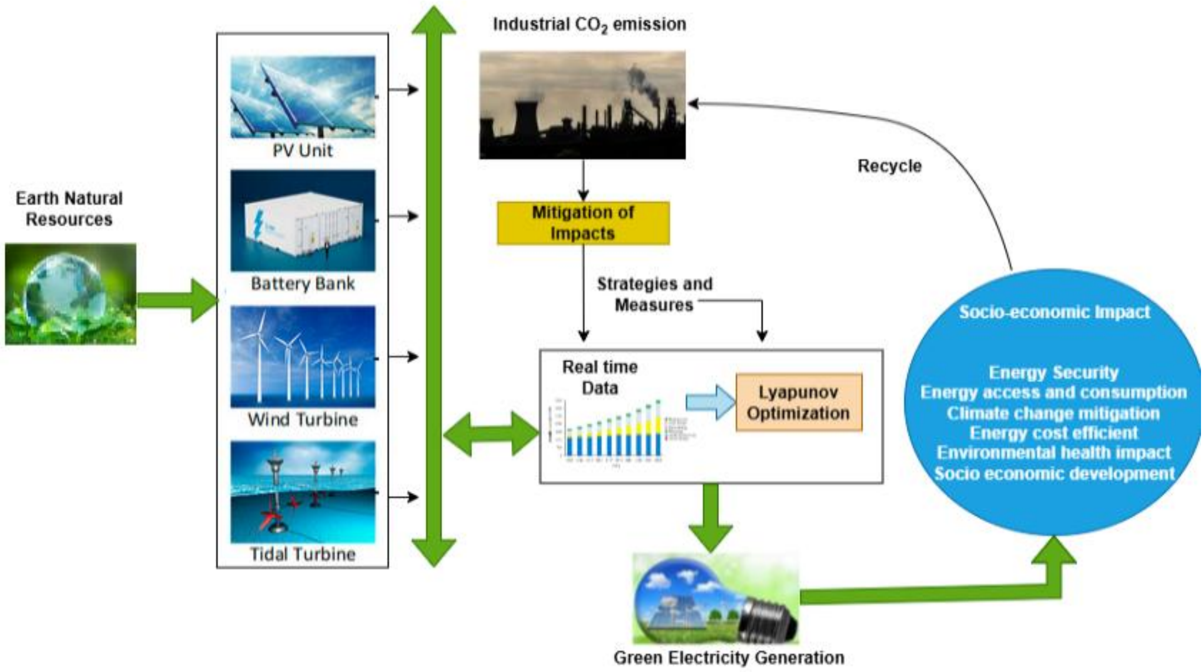

Figure 2: GHG mitigation strategy model

and planning of the RES is ascertained by using the genetic algorithm to accelerate the searching speed and to make decisions accordingly (Moreroa et al., 2024). Big data analytics enable timely real-time monitoring in remote places to meet the demand response programmes (Alghamidi et al, 2023). Elsayed Said et al. (2020) proposed RES with storage facilities to address grid integration capabilities by using advanced technologies, AI and deep learning for harvesting, weed detection and smart irrigation. However, maintaining traditional energy sources and controlling GHG emissions are crucial unless the system's stability is maintained. As a result, decentralised energy resources are more common in maintaining stability due to their sporadic nature (He et al., 2023). Energy storage systems are optimised using metaheuristic algorithms such as Cuckoo search, Grey wolf optimisation, ant colony optimisation and harmony search. An ameliorative whale optimisation algorithm can be used to optimise a ship's power using fuzzy rules (Jyoti et al., 2018). The optimisation is done through charge/discharge cycles in batteries and enhances converter and inverter performance. However, it lacks a control-theoretic framework that ensures system stability while optimising performance metrics over time. Zhou et al. (2021) have examined the resurgence of generative sources to help mitigate GHG emissions and improve environmental health.

Presently, South Africa's main power source is fossil fuels, which have detrimental effects on the environment. An estimated 30 m^3 of biogas is required to generate enough energy to run an average household. This study investigates the battery optimisation of a HES located in a remote place. The system model comprises various components, including the power-generating photovoltaic (PV) panel, wind turbine (WT) power and grid power. Solar and wind energy can be a challenge, but their sporadic nature is overcome by optimised battery storage. This study applies Lyapunov optimisation to control the system parameters and ensure the stability of a system. The suitability for real-time applications drives the research focus on Lyapunov optimisation, which enables adaptive energy dispatch, storage control and load scheduling.

3. Methods and materials

3.1 Battery storage model

A battery model is the first step in applying the proposed HES-LO approach. Battery storage is necessary to ensure a continuous power supply even during periods of low production. The energy storage solution is based on the charging and discharging of a battery.

3.2 State of charge

The state of charge (SoC) of a battery is its capability to store energy when it is available. SoC depends on the current state (t) and the previous state (t-1) of the battery, with an additional ratio $\frac{P_{BT}(t)}{V_{BT}(t)}$ of power and voltage of the battery with respect to change in time.

$$SOC(t) = SOC(t-1) \pm \frac{P_{BT}(t)}{V_{BT}(t)} \Delta t \tag{1}$$

3.3 Battery energy storage system

The stored energy is defined as

$$E_{BS}(t) = E_{BS}(t-1) + \eta \times (P_L - P_{PV} - P_{WT}) \tag{2}$$

where P_L is the load demand on the HES in Kw; P_{PV} is the generated electricity of PV panels; P_{WT} is the generated electricity of wind turbine.

Objective 1

The design process's first objective is to maintain the reliability of the HES. The energy index of self-reliance (EISR) is an index that helps to indicate whether a region is highly self-reliant on its energy resources or not. A high index score helps promote renewable energy development in low-income countries and is given as:

$$EISR = 1 - UME \tag{3}$$

where UME is the total unmet energy.

$$UME = \frac{\sum_{t=1}^{T}(P_{BT\,min} + P_d(t) - P_{WT}(t) - P_{PV}(t) - P_{SOC}(t))}{E} \tag{4}$$

The solar PV power output P_{PV} is determined using

$$P_{PV} = \eta_{PV} \times A_{PV} \times G_t \tag{5}$$

The WT power output $P_{WT}(\nu)$ is determined using

$$P_{WT}(\nu) = \begin{cases} 0 \; if \; \nu < \nu_{cut-in} \\ P_{rated}\left(\frac{\nu^2 - \nu^3_{cut-in}}{\nu^2_{rated} - \nu^3_{cut-in}}\right) if \; \nu_{cut-in} \le \nu < \nu_{rated} \\ P_{rated} \; if \; \nu_{rated} \le \nu < \nu_{cut-out} \\ 0 \; if \; \nu \ge \nu_{cut-in} \end{cases} \tag{6}$$

where $P_{SOC}(t)$ is the power at state of charge of a battery; T is the operational duration at time t; η_{PV} is the solar PV efficiency; area range is A_{PV}; solar irradiance is G_t; rated power of WT is P_{rated}; swept area is A_{WT}; rated wind speed is ν_{rated}, which depends on the WT cut-in ν_{cut-in} and $\nu_{cut-out}$ cut-out speed.

Objective 2

The second objective is to reduce CO_2 emissions by battery storage optimisation. CO_2 emission is calculated using

$$E_{CO2} = E_{WT} + E_{PV} \quad (7)$$

$$E_{WT} = (\sum_{d=1}^{365}\sum_{t=1}^{24}\eta_{WT}P_{WT}^{t})\delta_{WT} \quad (8)$$

$$E_{PV} = (\sum_{d=1}^{365}\sum_{t=1}^{24}\eta_{PV}P_{PV}^{t})\delta_{PV} \quad (9)$$

The implementation and design is based on HRES-LO to attain optimised energy efficiency and decrease emissions of GHGs. The system's design allows for flexibility in integrating energy storage, loss of power, over-production and cycling of charging and discharging.

3.4 Lyapunov optimisation framework

Lyapunov optimisation helps manage energy resources and allows for real-time decision-making to adapt to changing environmental conditions. The goal is to effectively handle and distribute the energy produced and stored, while maintaining system stability and dependability. A methodical way to accomplish this is given below.

3.4.1. Queue dynamics

The queue dynamics is employed in the evolution of virtual queue status when the power generation and load demand evolves.

$$Q(t+1) = \max\{Q(t) + P_{gen}(t) - P_{load}(t). 0\} \quad (10)$$

3.4.2. Lyapunov function

The Lyapunov function is the existence of a queue and is defined as

$$L(Q(t)) = \frac{1}{2}Q(t)^2 \quad (11)$$

3.4.3. Drift-plus-penalty

Lyapunov drift-plus-penalty is the difference between the current queue and the next queue with the penalty function $f\left(P_{gen}(t), P_{load}(t)\right)$ as load demand increases.

$$\triangle L\big(Q(t)\big) + V.f(P_{gen}(t), P_{load}(t)) \quad (12)$$

where $\Delta L(Q(t))$ is the drift and V is a trade-off parameter that balances the trade-off between queue stability and cost.

3.5. Optimisation problem

The Lyapunov optimisation problem is reformulated to minimise the drift-plus-penalty function.

$$\min_{P_{gen}(t), P_{load}(t)} \triangle L\big(Q(t)\big) + V.f(P_{gen}(t), P_{load}(t)) \quad (13)$$

subject to

$$C1: P_{gen}(t) > P_{load}(t) \quad (13a)$$

and

$$C2: SOC_{EES} \geq SOC_{EES}(t-1) \quad (13b)$$

The problem is converted into a single objective problem with the subjective constraints.

4. Experimental results and discussion

In this section, an experimental result shows the feasibility of the proposed HES-LO system for a remote area. The study evaluated an optimal energy management strategy to assess its efficiency. The proposed system is simulated and implemented using MATLAB. Table 2 describes the data used to run the simulation program.

Table 2: Simulation data

Module	*Parameter*	*Value*
PV module	Nominal power $P_{Nominal}$	75 W
	Optimal PV tilt angle (β)	50°
	Efficiency (η_{PV})	20%
	PV min area (A_{PVmin})	5 m²
	PV max. area (A_{PVmax})	50 m²
WT module	Nominal power P_{rated}	478.8 kW
	Swept area (A_{WT})	452 m²
	Rated wind speed (v_{rated})	12 m/s

The battery eases certain essential tasks and conditions so the grid can operate. The battery is used as a power buffer, which can store or release energy at time slot upon demand request.

Figure 3 shows how the solar PV power output and WT power output vary in terms of solar irradiance and wind speed in a range (0.8 kW to 8 kW) that is feasible for real-time implementation, depending on the application and scale. WT power output increases non-linearly, with wind speed reaching full power at rated speed, and staying constant until the cut-out speed (20 m/s). The parameters to get the maximum reachable output have been chosen. For reasons of feasibility and scalability, the rated power has been selected as 478.8 kW, swept area as 452 m^2, rated wind speed as 15 m/s, cut-in speed as $v_{cut-in} = 3\ m/s$,and cut-out speed as $v_{cut-out} = 20\ m/s$ to maintain the optimality.

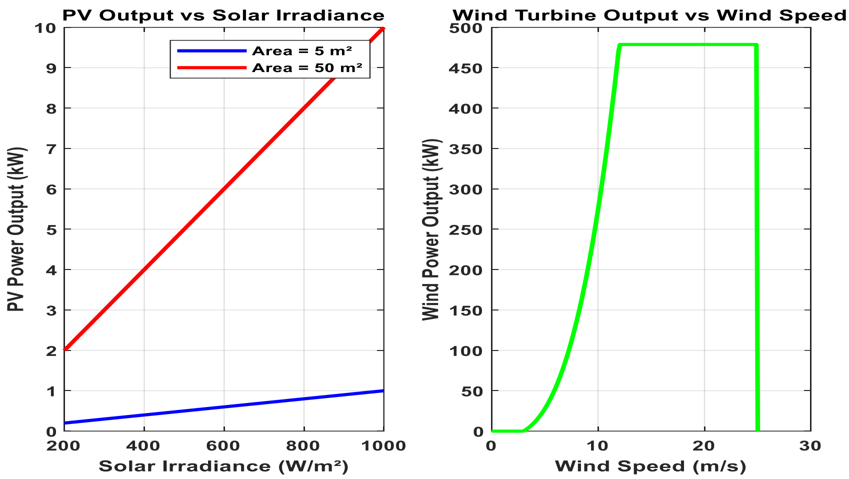

Figure 3: Solar PV and WT power output

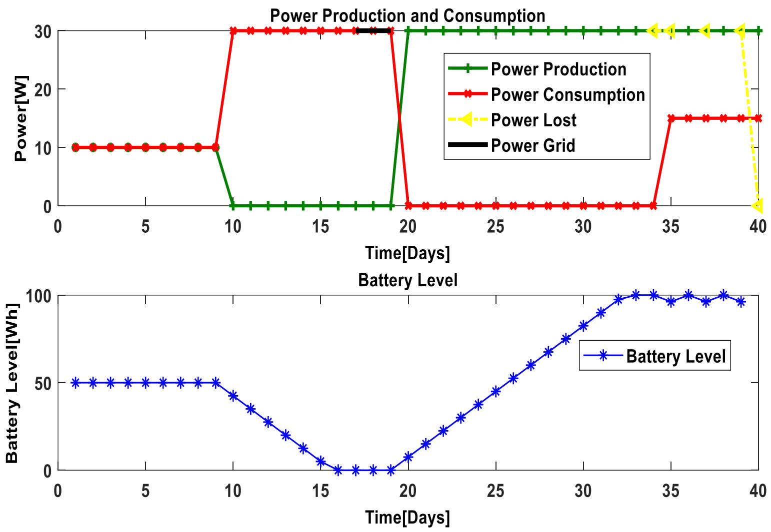

Figure 4: Energy flow and demand in terms of load profile

In this scenario, the batteries are arranged according to their size to perform the task of peak shaving and supporting service management. The battery sizes are based on a seasonal timeframe that results in excessive size. However, the requirements need to be fulfilled. The state of charge (SoC) of the battery is impacted by the battery characteristics, such as charging and discharging. The load profile performance of HES is illustrated in Figure 4. The blue line indicates the level of discharge power, that is, load power. The orange sections demonstrate the generated power of the sections from PV. The brown lines with dashes indicate the acts of releasing. In general, battery categorisations are determined by how deplorers charge them and by analysing their SoC. Power profiles offer important information on the optimisation potential.

The management approach governs how energy is distributed from different energy sources. Loads are loaded and unloaded, and is designed to enhance system performance based on specific goals (e.g. cost of operation, battery longevity, etc.). Dispatch analysis usually relies on the steady-state energy solution to maintain equilibrium. Figure 5 shows the Lyapunov queue of the HES-LO system under conditions such as overproduction and under-utilisation. This virtual queue is combined with a Lyapunov function and drift-plus-penalty analysis to manage energy in the system.

Table 3 references cost optimisation analysis, Table 4 is the comparative analysis based on various algorithms, Table 5 details the real-time applications and Table 6 references the comparative performance parameters of various algorithms proposed in the recent study.

The tables would likely present the results of the analysis, focusing on how the Lyapunov optimisation method's performance metrics are superior. The analysis examined the impact of the HES-LO algorithm on various cost factors within the HES, such as energy consumption, operational expenses and resource management.

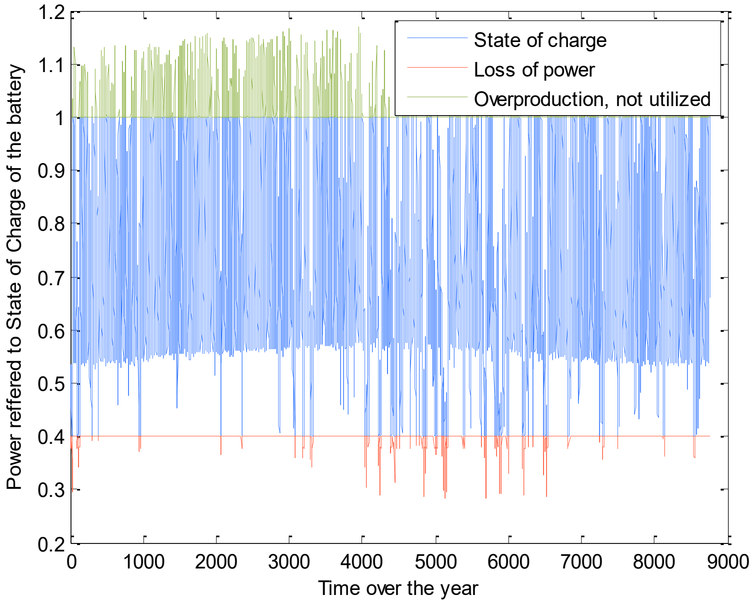

Figure 5: Power referred to the state of charge of the battery

Table 3: Cost optimisation analysis

Case study	*NPC (₹)*	*Charge battery (kWh/year)*	*Excess optimised energy (kWh/year)*
Solar PV	150 240	10 760	1 610
Wind WT	201 440	6 230	950
HRES =0.50×NPCSolar +0.50×NPCWind	175 840	8 495	2 560

Table 4: Comparative analysis of the proposed method

Optimisation method	*Suitability for HES*	*Advantages*	*Challenges*
Lyapunov optimisation	Best for real-time energy management	Adapts to power fluctuations Ensures system stability	Sensitive to parameter tuning
Mayfly algorithm	Efficient for grid stability and battery scheduling	Fast convergence	Requires tuning of genetic/PSO parameters
Genetic algorithm	Good for component sizing	Multi-objective problems	Slow convergence and computationally expensive
CUKO search	Suitable for microgrid planning	Strong global search ability	Slower than PSO
Gray wolf optimiser	Good for power dispatch optimisation	Fewer parameters	Can stagnate at local optima
Harmony search	Less effective for real-time operation	Good for initial system design	Slow for dynamic energy management
Flower pollination algorithm	Good for hybrid system sizing	Good exploration ability	Slower convergence for large-scale system

Table 5: Real-time application usage

Real-time application	*Area used*	*Output range*	*Realistic or not*	*Remarks*
House appliances (urban)	5-20 m^2	0.8-3.2 kW	Yes	Home appliances for lighting, air-conditioning and refrigeration
Rural home/farming	20-50 m^2	3.2-8 kW	Yes	Can support water pumps, TV, refrigerator, etc.
Telecom base station	10-30 m^2	1.6-4.8 kW	Yes	Typical mobile base station loading
Microgrid hybrid	50+ m^2	8+ kW	Yes	Community usage, hybrid with PV/WT/tidal

Table 6: Comparative analysis of the proposed method

Performance Metric	*Lyapunov optimisation*	*Mayfly*	*Genetic algorithm*	*CUKO search*	*Gray wolf optimiser*	*Harmony search*	*Flower pollination algorithm*
Energy efficiency (%)	93.5	92.1	89.2	91.2	92.1	88.2	90.1
Renewable utilisation (%)	95	93.4	90.2	93.2	94,2	89.0	91.4
Battery utilisation (%)	88.7	87.2	85.4	86.8	87.3	83.2	84.5
Cost reduction (%)	26	22	20	22	23	20	20
Convergence time (s)	0.21	0.35	1.86	0.95	0.42	2.12	1.25

The behaviour of a battery's SoC over time is presented in Figure 6, showing loss of power and over-production. SoC takes necessary actions during insufficient energy production or storage, resulting in power shortages. This is due to the variable nature of the charging and discharging cycles.

In Figure 7, the performance of Lyapunov optimisation analysis is shown and utilises the knowledge of queue length over time. The objective is to reduce the queue length; otherwise, the load demand will increase. The generated power and the load demand are shown in the upper part of Figure 7. The lower part shows the queue backlog, which represents unmet demand. It is minimised using a Lyapunov drift minimisation approach. The drift term represents the cost function to be minimised, and it influences the power dispatch from solar and wind systems. The sensitivity analysis is shown in Figure 8. It comprises the varying solar irradiance, varying wind speed, battery SoC, cost of energy and reduced CO_2 emission.

Figure 9 shows the EISR. This index is useful for taking control of household energy demand; This metric is used to stabilise energy supply-demand balance while optimising performance metrics like cost, battery usage and self-reliance. The three lines in the upper plot show how unmet energy compares with power demand and generated power over time. The lower plot shows a single bar indicating the EISR value of a proposed system. The reliability of the proposed system is 84.5%.

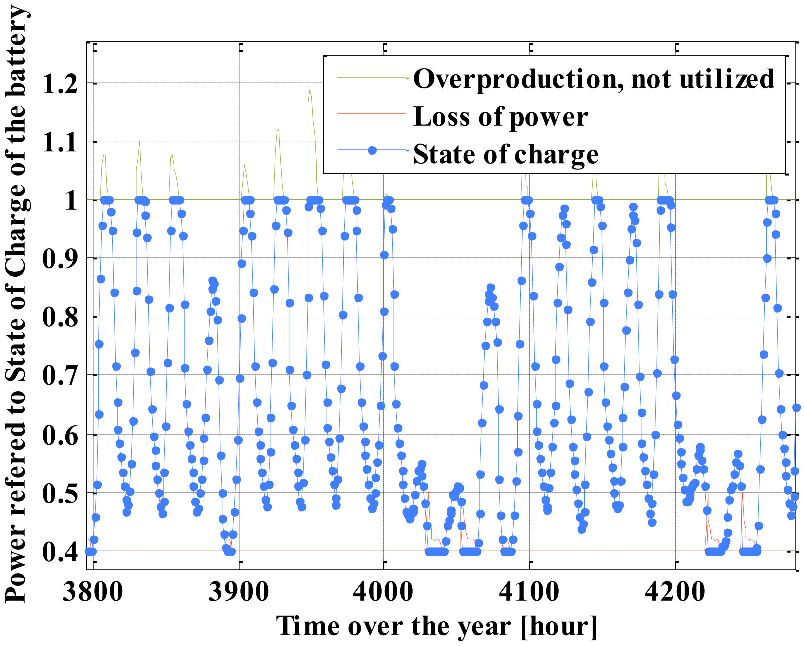

Figure 6: Battery's state of charge over time

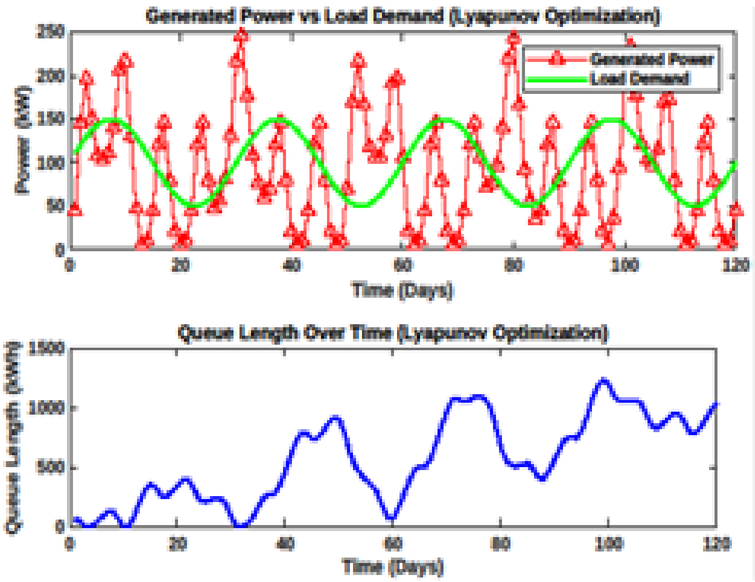

Figure 7: Lyapunov optimisation for the generated power and load demand

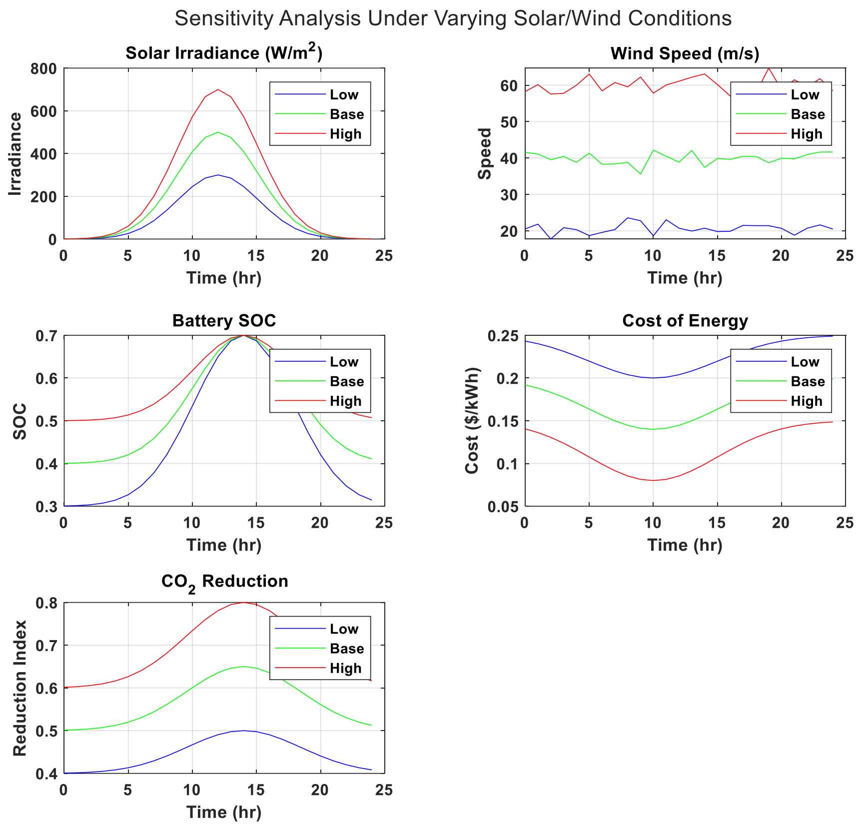

Figure 8: Sensitivity analysis under varying conditions

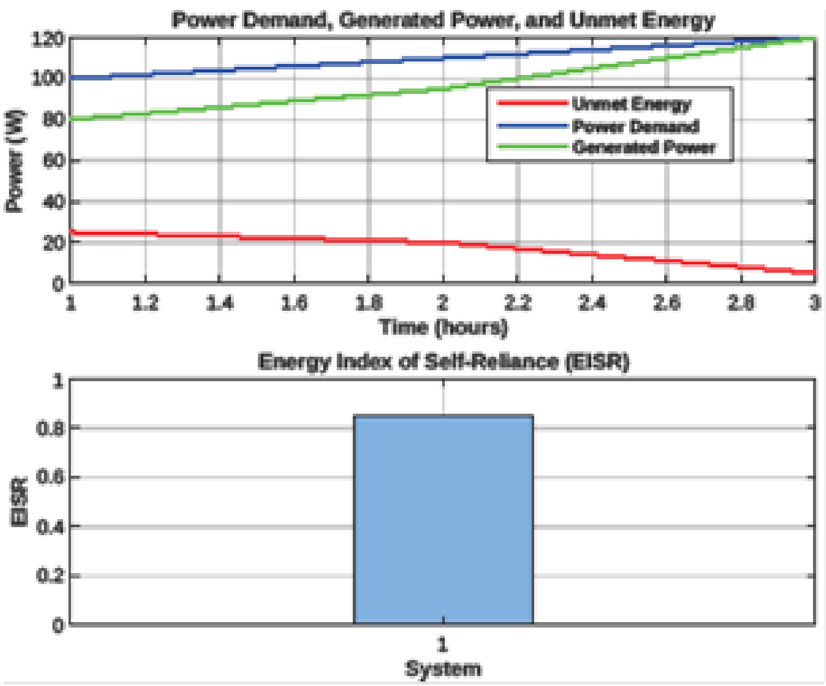

Figure 9: Energy index of self-reliance

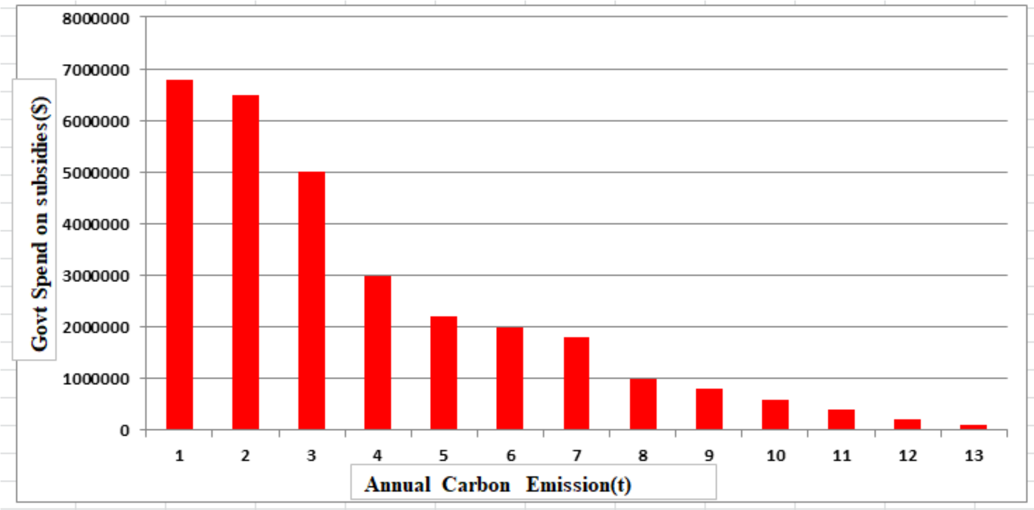

Figure 10: Annual carbon emissions

Figure 10 illustrates the activities of the HES under different subsidy policies. The solar power production by the HES rose substantially with the growth of traditional situations. The optimised HES-LO functions went from USD 0.07 /kWh to USD 0.09 /kWh with conventional systems, indicating that the design and operation of the HES will remain unaffected even if LO surpasses the limit. The present research showed that wind and solar PV systems have respective embodied carbon emissions of 17–26 gCO_2e/kWh and 43–72 gCO_2e/kWh (Xu, X et al., 2020). However, with the implementation of LO optimisation for sizing and controlling HES components, a country can lower its carbon footprint to meet its reduction target by 34-37% by 2050. Table 3 shows the cost optimisation analysis of HES and the 25% reduction in cost in India while using alternative energy sources instead of conventional energy sources and comparative analysis is reported in remaining tables from 4 to 6.

5. Conclusion

The analysis of sustainable energy and unmet energy is implemented using Lyapunov optimisation. The study analyses the state of charge of a battery and the load demand. Over-production and under-utilisation are managed using an optimised HES-LO system. This work analysed the mitigation of greenhouse gas emissions using clean HES energy. As per the simulation study, a battery bank is designed to optimise energy management. To increase system efficiency, the losses of power, over-production and under-utilisation of energy have been considered. Energy consumption is reduced by optimising energy flows and increasing efficiency. In this way, a low-income country can strengthen its economic resilience by reducing its dependency and protecting itself from external economic influences, such as geopolitical conflicts. The energy index of self-reliance confronts strategic planning and regulations. The takeaways from this analysis are as follows:

- Performance metrics such as energy efficiency, renewable energy source utilisation, battery utilisation, cost reduction and convergence analysis are shown to prove the effectiveness of the HES-LO system.
- Stability analysis is implemented using Lyapunov optimisation, and EISR is reported at 84.5%.
- The carbon footprint is reduced by 20% while using the hybrid systems.
- The mitigation of greenhouse gas emissions is optimised by using clean energy from varying sources.

Extensive work is needed in planning its implementation. The switch to renewable energies requires intelligent decisions, energy storage solutions and a successful transition to an independent energy supply.

References

Abd El Sattar Badr M. (2020) Hybrid Wind and Solar Systems Optimization Modeling, Simulation and Optimization of Wind Farms and Hybrid Systems. IntechOpen; http://dx.doi.org/10.5772/intechopen.89136. https://www.intechopen.com/chapters/69047

Ahmad, R. J. (2021). Economic dispatch in grid-connected and heat network-connected CHP microgrids with storage systems and responsive loads considering reliability and uncertainties. Sustain. Cities Soc. 73, 103101. doi:10.1016/j.scs.2021.103101

Alghamdi, A.S. (2023) Optimal Power Flow of Hybrid Wind/Solar/Thermal Energy Integrated Power Systems Considering Costs and Emissions via a Novel and Efficient Search Optimization Algorithm. Appl. Sci. 13, 4760. https://doi.org/10.3390/app13084760

Al-Rawashdeh, Hani, Al-Khashman, Omar Ali, Arrfou, Laith M., Gomaa, Mohamed R., Rezk, Hegazy, Shalby, Mohammad, Al Bdour, Jehad T., Louzazni, Mohamed. (2023) Different Scenarios for Reducing Carbon Emissions, Optimal Sizing, and Design of a Stand-Alone Hybrid Renewable Energy System for Irrigation Purposes. International Journal of Energy Research. 6338448 27 https://doi.org/10.1155/2023/6338448

Ates,E.Karaarslan, N. (2023) Investigation of Hybrid Renewable Energy Green House for Reducing Residential Carbon Emissions. International Journal of Thermo fluids. 21, 100558. https://doi.org/10.1016/j.ijft.2023.100558.

Balasubramanian K, Murugesan N, Samuel AMR, Sampath M. (2025) Lyapunov-based energy optimization for hybrid renewable energy system for coastal area. Proceedings of the Institution of Mechanical Engineers, Part A. 2025;0(0). https://doi.org/10.1177/09576509251333506

Elsayed Said Mohamed, AA. Belal, Sameh Kotb Abd-Elmabod, Mohammed A El-Shirbeny, A. Gad, Mohamed B Zahran. (2021) Smart farming for improving agricultural management. The Egyptian Journal of Remote Sensing and Space Science, 24(3) 971-981. ISSN 1110-9823, https://doi.org/10.1016/j.ejrs.2021.08.007.

Energy data Info (2023) https://energydata.info/dataset?vocab_country_names=IND.

He, Ya-Ling., Wang, Wenqi., Jiang, Rui, Li, Mingjia, Tao, Wenquan. (2023) Liquid-based high-temperature receiver technologies for next-generation concentrating solar power: A review of challenges and potential solutions. Front. Energy. 17(1), 16-42. https://doi.org/10.1007/s11708-023-0866-8

IPCC (2023) https://www.ipcc.ch/report/ar6/syr

Jyoti B. Fulzele, M.B. Daigavane.(2018) Design and Optimization of Hybrid PV-Wind Renewable Energy System. Materials Today proceedings. (1) 810-818 https://doi.org/10.1016/j.matpr.2017.11.151

Krishna Kumar Jaiswal. et al., (2022), Renewable and sustainable clean energy development and impact on social, economic, and environmental health. Energy Nexus, 7 100118. ISSN 2772-4271, https://doi.org/10.1016/j.nexus.2022.100118.

Mikalai Filonchyk, Michael Peterson, Haowen Yan, Andrei Gusev, Lifeng Zhang, Yi He, Shuwen Yang. (2024)Greenhouse gas emissions and reduction strategies for the world's largest greenhouse gas emitters. Science of The Total Environment. 944, 173895, ISSN 0048-9697. https://doi.org/10.1016/j.scitotenv.2024.173895.

Mikalai Filonchyk, Michael Peterson, Lifeng Zhang, Volha Hurynovich, Yi He.(2024) Greenhouse gases emissions and global climate change: Examining the influence of CO2, CH4, and N2O. Science of The Total Environment, 935, 173359, ISSN 0048-9697.https://doi.org/10.1016/j.scitotenv.2024.173359.

Moreroa, M., and Motshekga, S. (2024). The feasibility of using biogas generated from livestock manure as an alternative energy source: A South African perspective. Journal of Energy in Southern Africa, 35(1), 1-16. https://doi.org/10.17159/2413-3051/2023/v34i1a17021

Patel, K.Das, Narottam and Khan, Mohammed. (2019) Optimization of Hybrid Solar, Wind and Diesel Energy Systems from Economic Point of View. 29th Australasian Universities Power Engineering Conference (AUPEC), Nadi, Fiji. 1-6. https://doi/ 10.1109/AUPEC48547.2019.211861.

Rajee, S.A.M, Merline,A and Devi, M.M.Y.(2023)Game theoretic model for power optimization in next-generation heterogeneous network. Sing. Imag. Vid. Process.17(7) 3721– 3729.https:doi: 10.1007/s11760-023-02599-8.

Rui Yang, Kun Li, Ke Du, Boyang Shen. (2021) An ameliorative whale optimization algorithm (AWOA) for HES energy management strategy optimization. Regional Studies in Marine Science. 48 102033, ISSN 2352-4855. https://doi.org/10.1016/j.rsma.2021.102033.

Samuel Amalorpava Mary Rajee and Arulraj Merline. (2020) Machine intelligence technique for blockage effects in next-generation heterogeneous networks. Radioengineering, 29(3),555-563. https://doi.org/10.13164/re.2020.0555

Solar Farms India (2021) https://github.com/microsoft/solar-farmsmapping/blob/main/data/solar_farms_india_2021.geojson.

Thanh-Tuan Nguyen and Tobias Boström. (2021) Multiobjective Optimization of a Hybrid Wind/Solar Battery Energy System in the Arctic. Hindawi, | 8829561. | https://doi.org/10.1155/2021/8829561

Tripp, C. and Guittet, D. and King, J. and Barker, A (2022) A simplified, efficient approach to hybrid wind and solar plant site optimization. Wind Energ. Sci., 7, 697–713. https://doi.org/10.5194/wes-7-697-2022,

Vendoti Suresh, Muralidhar M., R. Kiranmayi. (2020) Modelling and optimization of an off-grid hybrid renewable energy system for electrification in a rural areas, Energy Reports. 6 594-604 ISSN 2352-4847. https://doi.org/10.1016/j.egyr.2020.01.013. (https://www.sciencedirect.com/science/article/pii/S2352484718304499)

Verma, M et al., (2021) Optimization of wind power plant sizing and placement by the application of multi-objective genetic algorithm (GA) in Madhyapradesh India Sustainable computing. Informatics and systems. 32, 100606. https://doi.org/10.1016/j.suscom.2021.100606.

Xu, X., et al., (2020) Optimized sizing of a standalone PV-wind-hydropower station with pumped-storage installation hybrid energy system, Renew. Energy, 147(1), 1418–1431. https://doi.org/10.1016/j.renene.2019.09.099.

Zhou, Y., et al.,(2021) A review on global solar radiation prediction with machine learning models in a comprehensive perspective. Energy Convers. Manag. 235 113960. https://doi.org/10.1016/j.enconman.2021.113960.