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Deep learning-enabled integration of renewable energy sources through photovoltaics in buildings

Munusamy Arun [a], Thanh Tuan Le [b,**], Debabrata Barik [c,j,***], Prabhakar Sharma [d], Sameh M. Osman [e], Van Kiet Huynh [f,*], Jerzy Kowalski [g], Van Huong Dong [h], Viet Vinh Le [i]

[a] Department of Mechanical Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Thandalam, 602105, India
[b] Institute of Engineering, HUTECH University, Ho Chi Minh City, Viet Nam
[c] Department of Mechanical Engineering, Karpagam Academy of Higher Education, Coimbatore, 641021, India
[d] Department of Mechanical Engineering, Delhi Skill and Entrepreneurship University, Delhi, 110089, India
[e] Chemistry Department, College of Science, King Saud University, P.O. Box 2455, Riyadh,11451, Saudi Arabia
[f] PATET Research Group, Ho Chi Minh City University of Transport, Ho Chi Minh City, Viet Nam
[g] Institute of Naval Architecture, Gdańsk University of Technology, Gdańsk, Poland
[h] Institute of Mechanical Engineering, Ho Chi Minh City University of Transport, Ho Chi Minh City, Viet Nam
[i] Faculty of Electronic and Electrical Engineering, Dong A University, Danang, Viet Nam
[j] Centre for Energy and Environment, Karpagam Academy of Higher Education, Coimbatore, 641021, India

HIGHLIGHTS

- Implementation of LSTM neural network into the energy management system.
- Robust prediction of PV power generation accuracy and improved monitoring.
- Optimizing energy management, efficiency, and cost by deep learning.
- Simulation results demonstrate improvements in sustainable energy practices.

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ABSTRACT

Installing photovoltaic (PV) systems in buildings is one of the most effective strategies for achieving sustainable energy goals and reducing carbon emissions. However, the requirement for efficient energy management, the fluctuating energy demands, and the intermittent nature of solar power are a few of the obstacles to the seamless integration of PV systems into buildings. These complexities surpass the capabilities of rule-based systems, necessitating innovative solutions. The research proposes a deep learning-based optimal energy management system designed specifically for home micro-grids that incorporate PV systems with battery energy storage, Enhanced Long Short-Term Memory (LSTM)-Based Optimal Home Micro-Grid Energy Management (OHM-GEM). Integrating an improved type of LSTM neural network called LSTM into the energy management system improves the reliability of PV power output predictions. The dependability of PV power production forecasts is increased by including a refined version of the LSTM neural network in the energy management system. The efficiency of the OHM-GEM system in maximiz-

* Corresponding author. Ho Chi Minh City University of Transport, Ho Chi Minh City, Viet Nam.
** Corresponding author. HUTECH University, Ho Chi Minh City, Viet Nam.
*** Corresponding author. Karpagam Academy of Higher Education, Coimbatore, India.
E-mail addresses: lt.tuan@hutech.edu.vn (T.T. Le), debabrata93@gmail.com (D. Barik), kiet.huynh@ut.edu.vn (V.K. Huynh).

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ing PV system integration into buildings is shown by the authors using simulated data. With considerable gains in energy efficiency, cost savings, and decreased reliance on non-renewable energy sources, the results highlight the possibility of this approach to forward sustainable energy practices.

Nomenclature and Abbrivation

Notations	Description
PV	Photovoltaic
OHM-GEM	Optimal Home Micro-Grid Energy Management
WTs	Wind Turbines
LSTM	Long Short-Term Memory
DSM	Demand Side Management
SMG	Smart Islanded Microgrids
SVM	Support Vector Machine
EHOA	Elephant Herding Optimization Algorithm
ML	Machine Learning
AI	Artificial Intelligence
DL	Deep Learning
MDP	Markov Decision Process
CEBADR	Collaborative Execute-Before-After Dependency-Based Requirement
ES	Energy Storage
SIES	Smart Integrative Energy System
HRES	Hybrid Renewable Energy System
IU	Individual User
l and *nl*	Linear and Non-Linear Functions
tp	Home's Total Power Usage (kWh)
ee	Building's Expected Electricity
cc	Correlation Coefficient
sc	Information Sharing Coefficient
Tq	The Total Quantity Of Labels
Lf	Loss Function
$(vr;\theta)$	Tweak The Network's Parameter Vector
Mx and *Mn*	Maximum and Minimum Value
cl and *fr*	Closest and Farthest Points
LB and *UB*	Lower and Upper Bound Functions,

1. Introduction

Due to the serious environmental pollution and fossil energy depletion, looking for alternative energy and fuels with clean and renewable characteristics is becoming an urgent issue for all countries in the world [1,2]. As reported in the literature, some renewable energy sources are being efficiently exploited such as solar [3], biomass [4], biofuels [5], wind [6], geothermal [7], hydropower [8], hydrogen [9], ocean energy [10]. Among these, solar energy is becoming increasingly popular as the globe seeks long-term energy solutions [11,12]. However, the sporadic and unpredictable character of these sources, together with the large variation of domestic energy demands, constitute considerable obstacles [13,14]. The core of the problem is determining how to cleverly and adaptably maximize the energy flow within these microgrids [15]. Conventional methods sometimes fail to balance energy production and consumption, leading to wasted energy, more expensive goods, and a lower ability to depend only on renewable sources [16–18]. By leveraging deep learning and recurrent neural networks (RNNs), Optimal Home Micro-Grid Energy Management (OHM-GEM) can solve this issue with its improved (Long Short-Term Memory) LSTM-based solution [19]. Importantly, LSTM networks have been incorporated in such problems [20], since LSTM networks are effective at modeling sequences and time-series data [21,22]. They are capable of predicting household energy use allowing quick distribution optimization and route modifications [23]. This enhanced micro-grid management approach seeks to intelligibly store or sell back any energy surplus during peak production periods [24]. Moreover, OHM-GEM is a robust and effective approach as it can adjust to changing user behavior, ambient circumstances, and various appliance efficiency [25]. By addressing the difficulty of efficient micro-grid energy management, OHM-GEM considerably helps lower carbon footprints and promotes energy sustainability in home environments by lowering energy costs [26]. By doing this, we can open the path for the broad implementation of renewable energy and the construction of technologically sophisticated, ecologically friendly homes of the future [27]. Fig. 1 shows a flexible microgrid system including photovoltaic (PV) panels, small-scale wind turbines (WTs), and energy storage devices either grid-connected or autonomously.

The microgrid may run either grid-connected or stand-alone. When isolated from the main grid owing to power interruptions or geographic isolation, the microgrid runs autonomously in standby mode [29]. The microgrid runs under one of many different conditions, hence maintaining power balance [30]. Energy self-sufficiency is promoted in equilibrium mode by the electricity produced by WTs and PV panels meeting local demand [31]. Second, while operating in surplus mode, the microgrid produces more electricity than it needs and may either store the surplus for later use or, if authorized, sell it back to the main grid [32]. Finally, energy is re-

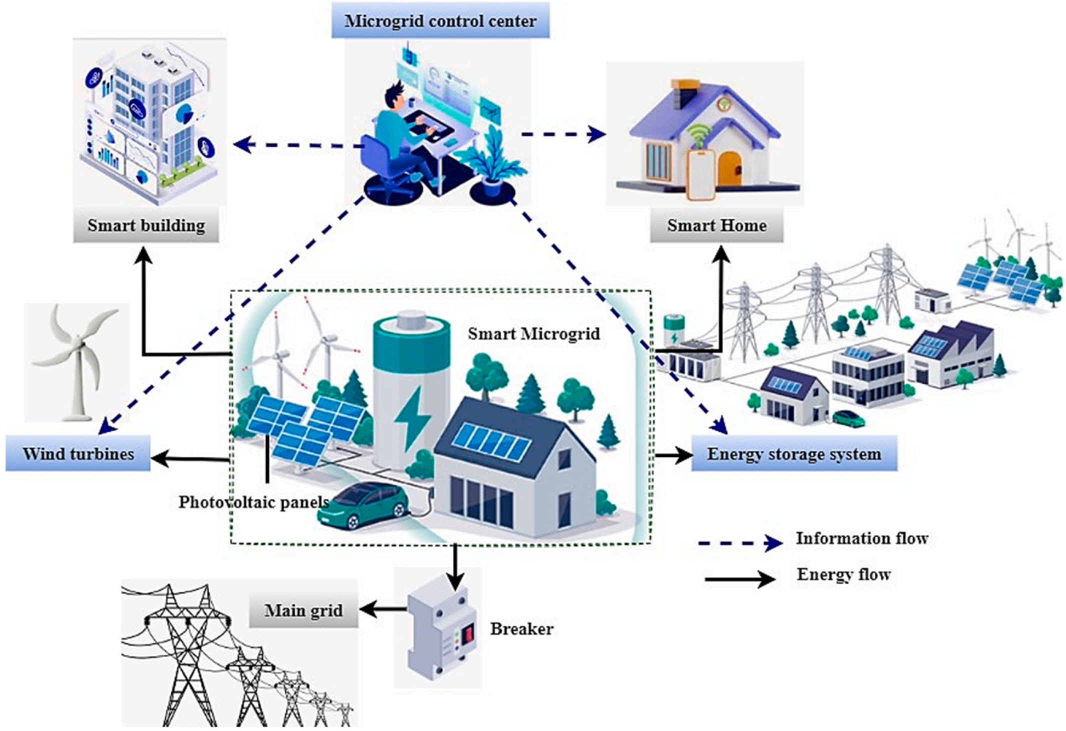


Fig. 1. Utilizing renewable energy sources in a microgrid (adopted and modified from Ref. [28]).

leased from storage or extra power sources in shortfall mode since the microgrid's generating capacity is below demand. However, the microgrid is fully integrated into the main power system while operating in grid-connected mode [33]. A single location termed a microgrid control center, manages the microgrid's operations. Real-time monitoring performed by this control center guarantees every microgrid component's reliability and optimal performance [34]. It allows easy switching between grid-connected and off-grid modes, improving power efficiency and stability [35]. This microgrid system may operate autonomously or in tandem with the larger power grid, making it a vital asset in today's energy infrastructure, as recognized by its contribution to increased resilience, sustainability, and agility in changing conditions. To overcome the obstacles to effective energy management in home microgrids, researchers have turned to the field of Enhanced LSTM-Based Optimal Home Micro-Grid Energy Management (OHM-GEM). Control methods relying on analog signals instead of computers were commonly employed to manage microgrids before developing sophisticated deep-learning algorithms. These systems used Rule-based algorithms and heuristics to regulate power distribution [36]. Although they were straightforward, they frequently had trouble adjusting to the ever-evolving requirements for energy and the unpredictable nature of renewable power.

Early initiatives sought to better anticipate and regulate energy use by using basic machine learning models such as linear regression and decision trees [37,38]. These models, however, lacked the complexity of temporal correlations and patterns shown in energy data. An important development in handling the time-series character of energy data was recurrent neural networks, widely popular LSTM networks. LSTM networks in particular allowed the researchers to enhance prediction and sequence modeling [39]. Still, it has challenges like controlling long-term dependence and adapting to rapidly changing settings [40]. Notwithstanding this development, the OHM-GEM and associated techniques still run against various challenges. First of all, collecting high-quality data for effective energy management is not an easy task. Problems in model performance might arise from faulty data collecting techniques, inadequate data, or absent background information. In addition, certain deep learning models, notably LSTM models, may drain power and computational resources. This intricacy might make deployment impossible in settings with limited resources. The fast variations in weather and energy consumption patterns call for microgrid management systems to be able to make decisions in real-time. Maintaining LSTM-based models flexible and responsive is an ongoing challenge. To guarantee it can operate with microgrids as small as one house or as big as a whole city, OHM-GEM must be scalable. The capacity of OHM-GEM to interact with and be included in already-existing energy infrastructure and grid systems will determine its success. These challenges must be surmounted if OHM-GEM is to fulfill its promise of revolutionizing home energy management and supporting sustainable energy habits, thus cutting costs, and so mitigating environmental effects. Based on the above discussion, the objectives of this research are as follows.

- This research aims to find ways to simplify implementing PV systems in buildings while increasing energy efficiency and sustainability.
- The research aims to use Long Short-Term Memory (LSTM) neural networks to improve the accuracy of predicting PV power generation, hence increasing the likelihood that renewable energy sources will be adopted.

- Importantly for sustainable property microgrids, the study seeks to establish the viability of the OHM-GEM system using simulations, highlighting its advantages in energy efficiency, cost savings, and less dependency on non-renewable energy.

This paper is organized as follows: Section II provides a literature review on Renewable Energy Sources using Photovoltaics in Buildings, highlighting the state-of-the-art and research gaps. Section III outlines the proposed enhanced LSTM-based OHM-GEM. Section IV presents the results and analysis of the experiments, as well as debates and comparisons to earlier approaches. The ultimate result is presented in Section V.

2. Literature survey

The study investigates many applications, including improving the sustainability and efficiency of energy systems and raising the accuracy of predictions for renewable energy. Collectively, they highlight the diverse character of present projects aiming at accelerating the dissemination of renewable energy. Abualigahet al. [41] invented computational intelligence methodologies to estimate renewable energy sources accurately, such as solar and wind power. The effectiveness of many DL and ML approaches is compared in a present taxonomy. The results imply that while efficiency, robustness, accuracy, and generalization remain challenges, learning methods can manage large datasets and parameters. For large datasets, learning techniques surpass conventional computer approaches. Theoretically, hybrid learning approaches—which include many approaches—which contain various methods—should be used to tackle energy-generating issues owing to accuracy. The importance of enhancing learning-based renewable energy forecasting techniques is underlined in the abstract.

To improve the performance of smart islanded microgrids (SMGs), Wang et al. [40] suggested demand-side management (DSM). While lowering power costs, SMGs including batteries and distributed photovoltaics increase energy efficiency. To generate strong battery operating choices, their research also used the Elephant Herding Optimization Algorithm (EHOA) and a Support Vector Machine (SVM). Using the EHOA-SVM approach thereby helped to lower the energy expenses by 11.2 % relative to the conventional approach. Customers gained from the cost reductions, and most crucially the demand was stabilized. Furthermore, the findings of the research showed that using machine learning and optimization techniques might improve SMG decision-making for better energy management at less expense.

As stated by Yao et al. [42], the perspective essay emphasizes the importance of using machine learning (ML) techniques in energy research to hasten the transition from fossil fuels to renewable energy sources. Emphasized for better renewable energy collecting, storage, conversion, and management are innovative materials, tools, and systems. Indices for evaluating ML-accelerated energy research strategies are presented in this study. These ML applications might considerably improve the efficiency of solar power systems. The viewpoint emphasizes various energy-related fields of study that can profit from ML applications, therefore illustrating the multidisciplinary character of this approach for solving the worldwide challenge of switching to renewable energy. They offered sustainable approaches to energy transition, automation, and artificial intelligence (AI) in the energy industry. Presented sustainable approaches for AI, automation, and energy sector transformation. It exposes the social and financial costs of inadequate incentives and bad energy industry decision-making policies. Examined are four primary elements of energy policy processes: decision-making during policy formation, management of policy implementation, data science and machine learning integration in energy systems, and sustainability needs. It looks at the difficulties of introducing artificial intelligence into the energy industry. Modern energy policies aligned with society's goals of achieving net zero and carbon neutrality may be developed and executed using this structure. The study offers a strategy for using artificial intelligence and automation to increase involvement in sustainable energy transitions without compromising efficiency or social justice, hence accelerating their pace. Bhansali et al. [43] reported the effectiveness of Deep Learning (DL) and Machine Learning (ML) methods, particularly those based on computational intelligence, which are used to develop precise energy conversion procedures for renewable energy sources. It shows the many criteria of energy-related data sets and their challenges. The advantages and disadvantages of many approaches to converting renewable energy are assessed in this study. The research closely investigates many approaches in search of effective renewable energy system solutions. Energy conversion and sustainability in renewable energy are raised using ML and DL methods. Yin et al. [44] recommended that integrated offshore wind and PV power generation systems must be optimized in variable meteorological conditions. To maximize electricity output and quality, they propose a hybrid regulation scheme taking offshore wind farm generator torque and PV array tilt angles into account. Under a partly observable Markov decision process (MDP), they simultaneously regulate the wind farm and PV array using a twin-delayed deep deterministic policy gradient (TD3) method for integrated power system management. Tests reveal that the TD3 method removes power fluctuation and increases power output. Through TD3 algorithm optimization, the integrated offshore wind and PV power systems maximize power production and smooth fluctuations. This study may help to increase the reliability and performance of renewable energy systems under demanding conditions. Awan et al. [45] provided solutions for the inherent systems connected to the smart grid in the smart cities and green energy management framework. A novel machine learning method based on particle swarm optimization, Collaborative Execute Before After Dependency-Based Requirement (CEBADBR), is presented to address the problems of several intrinsic systems. Two steps comprise the CEBADBR method: first, PSO evaluates a randomly produced load population over 90 days; second, continual load profile tuning over 24 h. Regarding % cost reduction, peak-to-average ratio, and power variance mean ratio, simulation results suggest that the proposed CEBADBR technique performs better than standard particle swarm optimization and inclined block rate methods.

Collectively, the research studies herein highlight the revolutionary role that CI, ML, and AI play in fostering the development of renewable energy technology, optimizing energy systems, and disseminating sustainable energy practices. The present study especially combines such multidisciplinary methods to hasten the transition towards environmentally friendly energy sources. Achieving energy efficiency, economic reductions, and less dependence on non-renewable energy sources presents challenges for present solutions. The OHM-GEM system adds a sophisticated LSTM network to improve energy distribution real-time optimization. Offering a more flexible and effective solution than conventional energy management techniques, this invention greatly increases forecasting accuracy for both supply and demand.

3. Model development

Integration of PV systems into buildings has lately attracted great interest as a sustainable approach to meet energy requirements [46]. A branch of artificial intelligence, deep learning has become a powerful tool for maximizing the efficiency of linked systems. Deep learning algorithms might be used by PV systems to maximize energy collecting in all types of conditions to predict solar irradiation and generation patterns [47]. Therefore, carefully managing the flow of electricity may reduce waste and dependency on the traditional power grid at the same time it can maximize storage and use [48]. The interconnected components of a solar PV power plant are illustrated in Fig. 2.

3.1. Components of home micro-grid energy management system

PV Panels, or Photovoltaic Cells: A solar power plant depends critically on PV panels as they use semiconductor materials such as silicon to collect sunlight and generate direct current (DC) electricity. Monocrystalline, polycrystalline, and thin-film PV panels are among its many forms; each has a unique cost and efficiency profile. The needed energy output and available space determine the panel count and size.

Inverter: Although most appliances and the power system run on alternating current (AC), PV panels provide DC electricity. By separating DC from the grid during failures (anti-islanding), an inverter improves system safety and transforms DC into AC electricity. By use of maximum power point tracking (MPPT), it also maximizes power output. String inverters for several panels, microinverters for single panels, and central inverters for large-scale projects are a few of the many kinds of inverters.

Devices for storing energy: Excess solar-generated power is stored in batteries for use on cloudy days or at night. This storage lowers grid reliance, raises solar energy self-consumption, and offers backup power during outages. In solar systems, common battery kinds include lead-acid and lithium-ion.

Voltage Regulator: Overcharging or too strong discharge causes battery damage; charge controls stop this They control the power flow from PV cells to batteries, therefore guaranteeing effective charging and improving battery lifetime. Other controls include temperature compensation.

Balancing of the System: Proper wiring, cabling, and mounting frameworks are essential for the reliability and efficiency of the solar power plant. Durable and adjustable mounts help maximize solar energy capture."

System for monitoring and controlling: Analysis tools and sensors allow one to monitor system performance in real time. This guarantees consistent maintenance, improves energy economy, and helps troubleshoot. Disconnect switches and surge protectors, which guard the system from power surges and lightning strikes, are part of safety equipment. When solar production is inadequate, backup generators - usually run on diesel or natural gas - may be included in solar power plants to guarantee ongoing energy delivery. PV panels for energy collection, inverters to translate DC to AC, energy storage systems, charge controllers for battery management, and balancing components to guarantee dependability, efficiency, and safety define a solar power system. By means of solar power management, battery storage, and building energy consumption optimization, the system seeks to lower dependency on non-renewable energy sources and increase energy efficiency. Solar panels transpose solar energy into electricity.

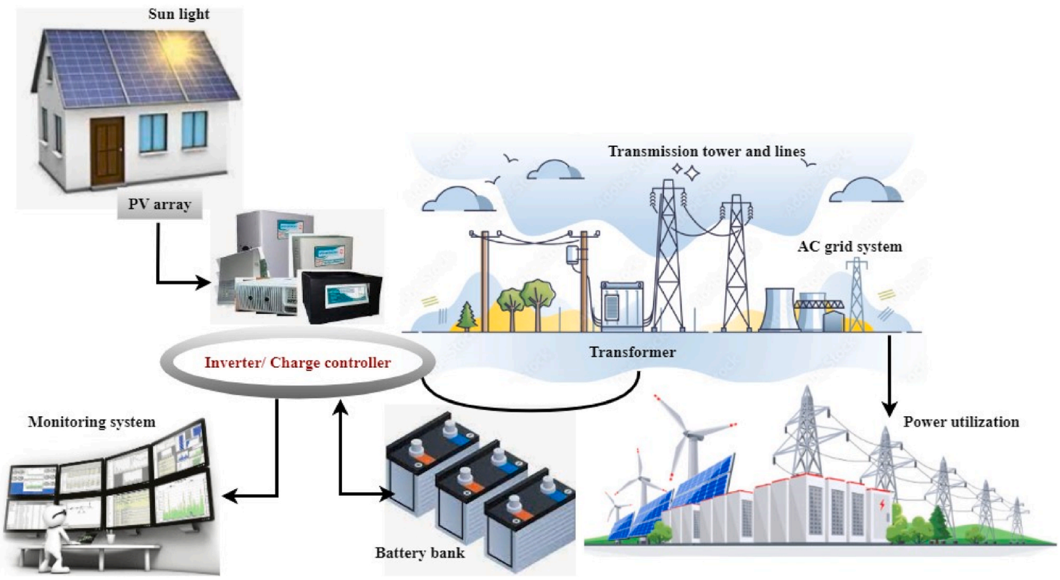


Fig. 2. Components of solar PV power plant.

Although energy obtained fluctuates with cloud cover and time of day, rooftop solar panels are a reasonable choice for using renewable energy. Fig. 3 shows utilizing deep learning how the "Enhanced LSTM-Based (OHM-GEM)" technology combines solar PV panels into structures.

3.2. LSTM neural network

To meet the challenges of forecasting solar power generation, this approach uses deep learning using a Long Short-Term Memory (LSTM) neural network. A kind of Recurrent Neural Network (RNN), LSTM networks are ideal for detecting patterns and temporal links in data [49–51]. Handy for managing temporal patterns and variations in photovoltaic (PV) power output, this specialized LSTM model uses past solar power data, the LSTM network forecasts future PV power production, therefore enabling the system to predict solar energy availability [52]. Effective energy management depends on this aptitude for anticipating. Based on expected PV power generation and energy consumption, the Optimal Home Micro-Grid Energy Management (OHM-GEM) system combines these projections to make educated choices about energy storage and utilization, therefore optimizing total energy management.

3.3. Energy Demand Prediction

Energy Demand Prediction: The OHM-GEM system forecasts PV energy production and building energy consumption. This projection takes the time of day, current building occupancy, and previous energy usage patterns among other factors. Batteries are a component of an energy storage system designed to solve the output-to-consumption gap in solar power. The system monitors battery status and decides whether extra solar energy should be kept on hand or released to meet building demands. Maximizing solar power usage and storing extra energy when the sun isn't out is very crucial. Building load is the whole energy consumption of a construction, including that resulting from heating, cooling, and lighting systems. Maximizing efficiency and lowering dependency on non-renewable energy sources depend on good load management. Fig. 4 shows the overall suggested system's design LSTM. The suggested architecture is grounded on a methodical approach to researching information on energy generation.

First, power generation data is gathered from numerous sources. The second step is comprehensive pre-processing, which includes fixing any data peculiarity and ensuring consistency [53]. The next phase involves extracting critical features from the processed data, essential for identifying important patterns and dependencies. In the last step, these inputs feed an LSTM network. The LSTM network produces outputs at this step using these characteristics. The performance of the network in generating correct and consistent solutions for different natural language tasks is improved by its capacity to record contextual information from past and next sequences. Especially bidirectional LSTM networks are good at deciphering intricate temporal patterns [54]. This design provides strong insights and prediction powers in energy production data analysis, therefore supporting more exact decision-making and system optimization. Electricity is produced by renewable energy sources (RES) including wind, hydroelectricity, geothermal, solar, tidal, and biomass. Smart grids and other distributed generating systems provide this energy to companies and residences. With sensors placed in smart grids to track and document power output and consumption, the suggested method analyses wind and solar power generating data using LSTM networks.

3.4. Deep learning model development through LSTM network

To forecast future power production and consumption, DL models are trained using past data including energy generation and consumption. Issues like noise and missing numbers during data collection create some unknowns in the data. These deviations are eliminated by pre-processing techniques. Normalizing data to fit for model training benefits from an average filter. Dealing with missing data benefits from the replacement technique, in which values from the past replace missing values. Deep learning models allow

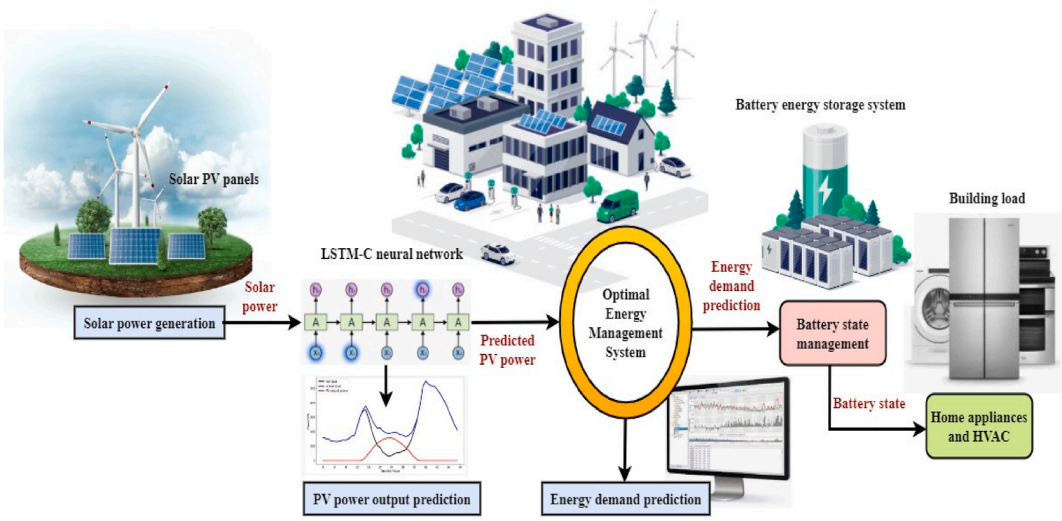


Fig. 3. Optimal home micro-grid energy management.

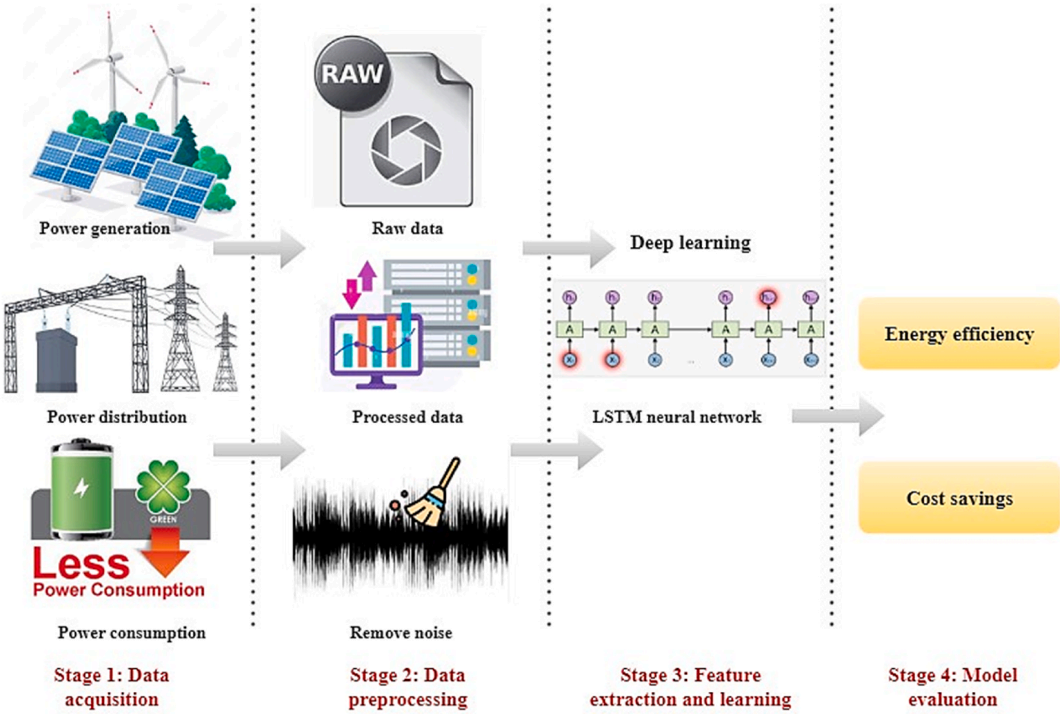


Fig. 4. Process flow of Long Short Term Memory (LSTM).

one to map desired outputs from input data. Input data comes with many variables in different forms and sizes [45,53]. Representing a problem with varying magnitude and distribution of the input variables might be challenging. Consequently, DL models learn rather high values for weights when the values of the input variables are big and vary much.

The model becomes unreliable and produces subpar results because of this. Similarly, a model with high weight values performs worse across the board and has a larger generalization error. Also, the learning process becomes unstable, and the error gradient becomes substantial when the output variable has a wide range of values. Because of this, scaling the data from input to output is crucial when training DL models. The abovementioned issues can be addressed by normalizing the data in the input and output variables to a range between 0 and 1. The system performance analysis is expressed in Eq. (1) [55,56]:

$$\left(\widehat{E}_{te+2,}\widehat{E}_{te+2,}\ \dots,\widehat{E}_{te+24}\right) = LSTM\left(P_{te-k+1},\dots,P_{te-1,}P_t\right) \tag{1}$$

The LSTM network is an enhanced version of the RNN that adds memory cells and many control gates that overcome the restrictions. Using memory cells, LSTM networks can take advantage of the persistence of temporal dependencies and guarantee the dissemination of data through successive time steps within the same network architecture using Eq. (1).

The sigmoid activation function generates a number between 0 and 1 for each gate value. The activation function of the hyperbolic tangent is used to forecast the cell's output. The forecasting accuracy of various applications is negatively impacted by the fact that the unidirectional LSTM algorithm analyses the input sequence information at every time point based on the knowledge contained in the past and ignores future input by applying Eq. (2). The efficiency metrics analysis is expressed in Eq. (3) [55,56].

$$A_f = f_g.f_{a-1} + \left(1-f_g\right).tanh\left(\overrightarrow{Wt}_i\left[\overrightarrow{cs}_{te-1}\right] + te\right) \tag{2}$$

$$Pr_{te} = \sigma + \left(\overrightarrow{Wt}_i\left[\overrightarrow{cs}_{te-1}\right] + te\right) + m_i\Big) + tanh\left(\overrightarrow{Wt}_i\left[\overrightarrow{cs}_{te}\right]\right. \tag{3}$$

This study aims to improve typical LSTM networks by use of a bidirectional learning method. This approach lets the network use past and future data within the sequence, hence enhancing performance. Demand response modeling seeks to reduce costs while guaranteeing customer satisfaction by the use of minimums. The advancement of renewable energy systems, energy storage methods, and energy conservation depends critically on the design of smart, active buildings. Good management and design techniques help smart buildings to maximize the usage of renewable energy sources (RES) [57]. Furthermore supporting the development and usefulness of smart, active buildings are sophisticated building energy analysis and forecasting methods.

3.5. Building energy model based on environmental conditions

The three main types of building energy simulations are supply-side models, demand-side models, and hybrids of the two. Building modeling of energy is a multi-criteria problem that requires taking into account both energy use and generation at the same time. Variables such as consumption patterns, climate (e.g., humidity and cloudiness), atmospheric conditions (e.g., wind and pressure), and ES capacity are critically important to the modeling process. Buildings have seasonal fluctuations in energy consumption and supply per hour weekly [58,59]. However, putting environmentally friendly solutions into practice is difficult. For instance, solar radiation and heat levels play a role in the unpredictability of PV outputs [60].

Wind energy is considered a promising clean energy based on its advantages such as no pollution, abundance, and low cost. The issue of capturing wind energy comes from the fact that its speed and direction are always shifting. Hybrid renewable energy systems (RES) combine two or more RES to produce electricity and have distinct benefits. Combining wind power with solar PV, for example, can greatly boost the sustainability of the environmentally friendly energy supply system, as wind energy can be found even during overcast hours and at night [58,61]. The successful incorporation of RES and the reduction of energy conversion losses are two of the biggest obstacles to creating smart active buildings, even though energy efficiency, energy costs, and environmental concerns are driving forces. A smart integrative energy system (SIES) that considers energy production and use systems is necessary to face and overcome these obstacles. Smart integrated energy systems are depicted in Fig. 5.

3.6. Smart hybrid integrative energy system

A Smart Integrative Energy System (SIES) plans to create an optimal energy supply bundle using non-renewable energy sources. A SIES regularly assesses energy demand and supply levels to reduce the amount of energy supplied by non-renewable resources. High resolution of consumption of energy and energy generation datasets, such as an hour or half-hourly datasets, must be present to allow SIES for intelligent, active building energy management. Energy modeling for the smart building that includes RE sources is highly complex and non-linear. Because of the varying nature of weather data and the unpredictability of daily and seasonal energy production patterns inherent to renewable energy [62]. Energy storage, solid biomass-fueled micro-combined Heat and Power (micro-CHP) systems and solar technologies are all part of a Hybrid Renewable Energy System (HRES) that Fig. 6 demonstrates the compelling need for hybridizing RES and provides valuable insights into achieving. The search for long-term energy solutions that can satisfy the wide range of building energy demands without reducing efficiency or dependability motivates this strategy.

Micro-CHP systems powered by solid biomass are central elements of the HRES. These systems are well-suited to satisfying the varied energy needs of buildings since they provide a sustainable and efficient means of producing electricity and heat. Two forms of renewable energy are used in this HRES by integrating micro-CHP systems with solar technology. Micro-CHP systems, which enhance the power and thermal energy supplied by solar PV panels and solar thermal systems, produce electricity and heat from solid biomass fuels. This mix ensures a consistent energy supply even with low solar output and improves energy generation [63,64].

Dynamic HRES design and operation depend critically on multi-objective optimization methods. These methods strike a mix of system dependability, environmental impact, and economy. The HRES can adjust to different conditions by using real-time meteorological data, therefore optimizing energy output and storage to satisfy the energy consumption of the building. This data-driven approach makes the system more dependable and efficient, therefore rendering it a long-term, sustainable energy source. To satisfy electricity, space heating, and domestic hot water demand, the study emphasizes the requirement of buildings combining solid biomass-

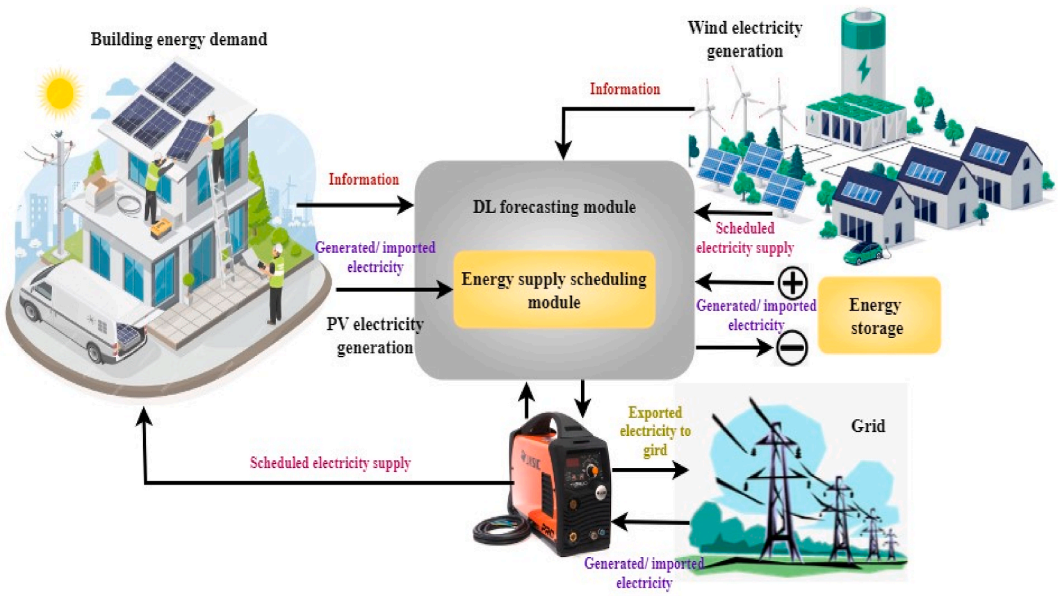


Fig. 5. Deep learning-based optimal energy management system.

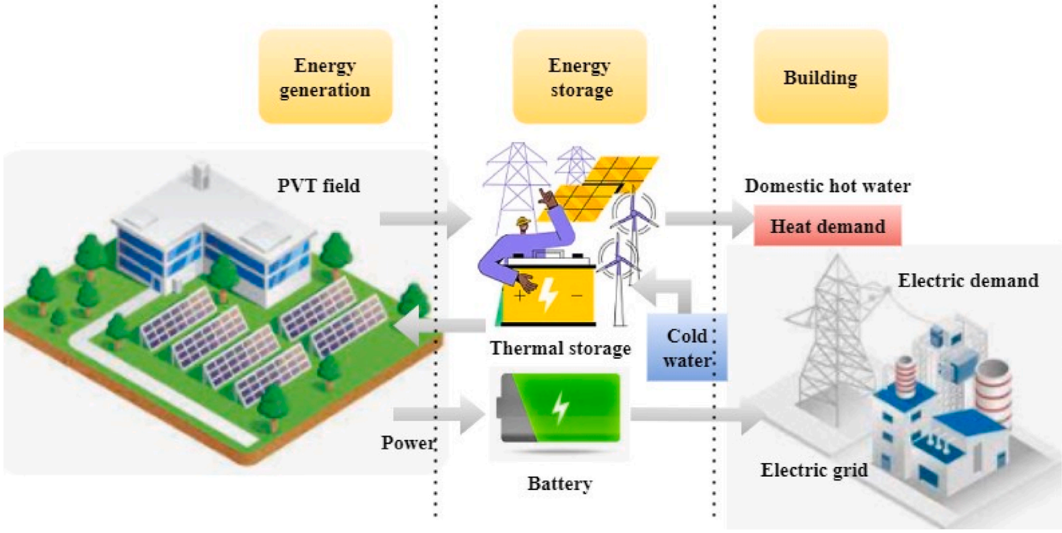


Fig. 6. Thermal storage of renewable energy in buildings.

fueled micro-CHP systems with solar technologies, like photovoltaic-thermal (PVT) systems. When combined with micro-CHP systems, PVT systems may produce hot water and thermal energy as well as power, therefore offering space heating. This complimentary strategy guarantees complete energy coverage and increases the general HRES' efficiency. More system-specific measurement data is thus required if the goal is to maximize HRES' dependability and performance. System modifications and maintenance may be informed by real-time monitoring of elements like energy production, storage levels, and building energy use. Furthermore offered is a stochastic optimization approach for energy management. This approach incorporates these variances into the optimization process, therefore allowing for the inherent uncertainties in energy output and consumption. Stochastic optimization helps the HRES to become more robust and adaptable, therefore allowing it to react sensibly to changing operational and environmental situations.

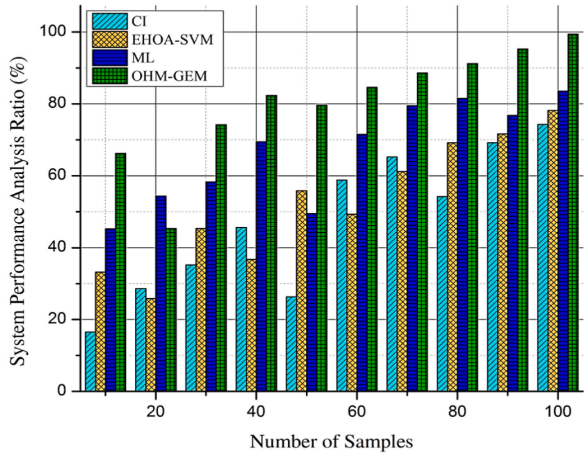
4. Results and discussion

4.1. Performance analysis for OHM-GEM and LSTM

This research compares the OHM-GEM system to a standard LSTM approach in domestic energy management. Fig. 7a and b depict the building energy system performance analysis in a comparative manner for OHM-GEM and LSTM, respectively. In the case of sustainable and cost-effective home energy management, OHM-GEM offers an effective solution by optimizing solar energy utilization, management of varying loads, and grid power exchange. OHM-GEM allows informed decision-making for consumption and decision-making by precisely projecting solar power production using sophisticated deep-learning approaches. The system's capacity to efficiently utilize solar energy is a critical factor in the evaluation. The OHM-GEM system additionally demonstrates its load optimization abilities. It does this by determining how much energy a home will need and comparing that to the amount of power generated by solar panels and stored in batteries. By doing so, it reduces energy costs by decreasing the consumption of the central grid and other supplied non-renewable energy sources. In addition, this OHM-GEM system is capable of monitoring the dependency on the storage battery and how well it is working. OHM-GEM effectively regulates the battery's state of charge (SOC), allowing its potential to be consistently realized. This feature likewise improves power dependability and extends the battery's service life [45,65]. The system's reliability stems from its response to shifting conditions and flexibility in accommodating varying load requirements and weather patterns. The simulation results reveal that OHM-GEM and LSTM could work in practice, highlighting potential benefits like increased energy efficiency, monetary gains, and a minor environmental impact. Comparing the system performance between OHM-GEM and LSTM yields, OHM-GEM gives a higher value of performance rating of about 96.3 %, whereas LSTM gave about 94.8 % efficiency. The small deviation in the performance between OHM-GEM and LSTM represents accuracy in the analysis and feasibility for real applications.

4.2. Power generation analysis for OHM-GEM and LSTM

To guarantee the effective use of renewable energy sources, the system makes accurate predictions of solar energy generation using cutting-edge deep learning techniques. These exact projections provide homes with a solid basis from which to make wise choices about distribution, storage, and energy usage. OHM-GEM shines in matching the changing energy use of individual residences with the power-producing capability. It maximizes real-time energy use to match expected solar output, therefore lowering dependence on grid power during peak demand. Along with reducing the related environmental effects, this method helps to minimize energy expenses. Effective battery management is fundamental to OHM-GEM's power control. Through rigorous monitoring and regulation of the state of charge (SOC), the system guarantees the effective use of stored solar energy all day. This lets the system maximize solar energy retention for use during low or nonexistent sunshine, hence improving the household's energy independence [66].



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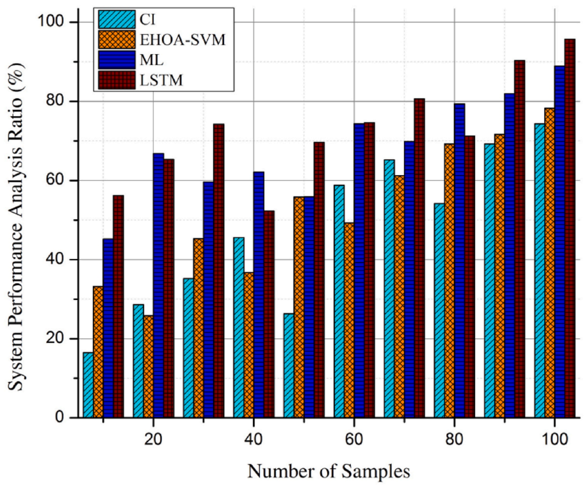


(b)

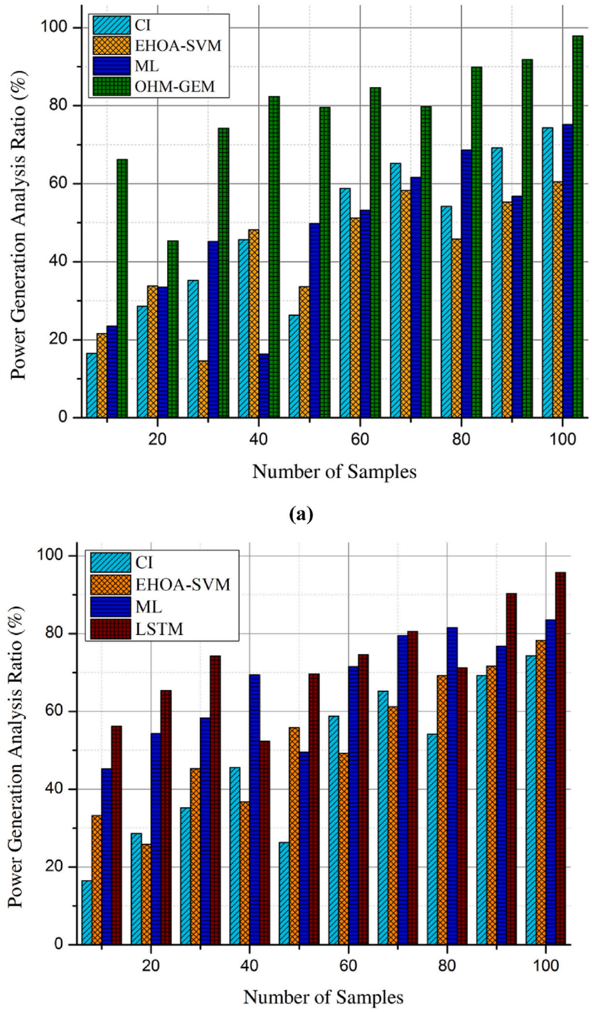
Fig. 7. Building Energy System Performance Analysis is compared with (a) OHM-GEM; and (b) LSTM.

In addition, OHM-GEM allows two-way energy flow between the microgrid and the main grid employing flawless grid connectivity. When generation outpaces demand, homes may sell extra power; when needed, they can buy electricity from the grid. This reciprocal communication serves to save expenses and improve the dependability of the power source. The system's versatility in changing load profiles and response to diverse environmental circumstances helps it to effectively control power generation. As shown in Fig. 8a and b, simulations illustrate how well OHM-GEM and LSTM might be used in the actual world to provide significant gains in environmental impact, cost savings, and energy economy. With a 97.3 % accuracy in power-generating forecasts, the system beats a regular LSTM model with 95.8 % accuracy. Promoting cleaner, more efficient, and reasonably priced energy solutions, OHM-GEM models sustainable energy management in household microgrids.

4.3. Energy cost analysis

Energy cost analysis within the OHM-GEM system shows a notable movement towards reasonably priced, eco-friendly residential energy consumption. The sophisticated predictive features of the technology let homeowners maximize the usage of solar energy sources, therefore lowering their energy costs. Forecasting peak solar output allows OHM-GEM to assist homes plan energy-intensive chores for maximum solar output or less expensive grid power during off-peak hours. Further cost reductions come from the bidirectional connection connecting OHM-GEM to the grid. Should the production of a house surpass its use, the system may sell the extra back to the grid. On the other hand, it may purchase energy when prices fall, therefore maximizing cost-effectiveness. OHM-GEM lowers home energy expenses by dynamically changing energy use to match real-time price swings.

OHM-GEM and LSTM adjust to changing energy costs and real-time usage patterns by executing power-hungry activities when electricity is least costly as depicted in Fig. 9a and b, respectively. This method of adaptive cost control aids in reducing household energy use. OHM-GEM lets homes choose reasonably priced energy by combining grid interaction, battery storage, and renewable energy sources. This study shows how OHM-GEM may help to provide affordable, environmentally friendly energy sources for domestic



(a)

(b)

Fig. 8. (a) - Power Generation Analysis is compared with OHM-GEM; (b) - Power Generation Analysis is compared with LSTM.

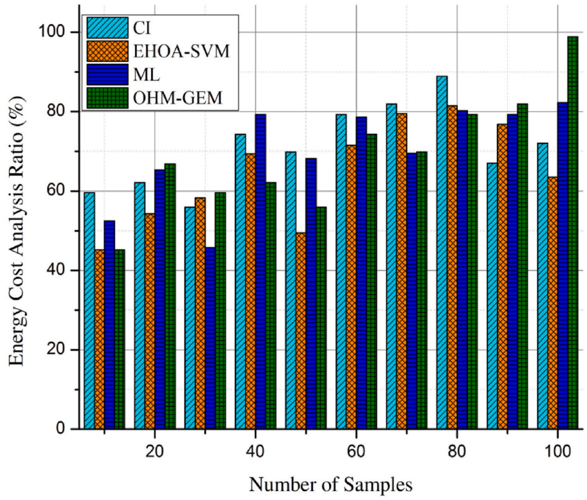
uses. Having a 98.9 % efficiency over OHM-GEM and a 95.7 % efficiency above ordinary LSTM models, the Energy Cost Analysis shows that OHM-GEM maximizes energy expenses. (For clarity, more specifics on these measures should be included).

4.4. *Analysis of efficiency*

The degree to which microgrid controls and distributes produced energy for domestic use determines its level of efficiency. Employing accurate solar power projections and optimal demand-response, OHM-GEM increases efficiency, therefore minimizing energy waste and maximizing the use of produced electricity. By controlling the State of Charge (SOC), its battery management technology prevents overcharging and too strong discharge, therefore lowering energy losses and increasing battery life. Effective grid interactions are vital as OHM-GEM constantly moves between grid and microgrid power depending on real-time energy needs and market pricing, therefore lowering the total energy costs. The ability of the system to adjust to load profiles and weather circumstances improves efficiency even further via real-time energy use optimization [67,68]. OHM-GEM regularly changes its energy management techniques to maximize efficiency and reduce waste both during and off-peak hours. Examining the performance of OHM-GEM as shown in the Efficiency Metrics reveals its efficiency in residential microgrid energy management optimization. Through optimal utilization of solar power, energy storage management, and grid interface optimization, both OHM-GEM and LSTM help to create a more cost-effective, ecologically sustainable energy future Fig. 10a and b, respectively. This all-encompassing method for efficiency fits more general objectives of lowering carbon emissions and advancing more environmentally friendly household energy sources. Comparatively to LSTM's accuracy rating of 97.7 %, OHM-GEM shows a dependability rate of 99.4 % in the efficiency metrics study.

4.5. *Grid Power Exchange Analysis*

The transforming impact of the Grid Power Exchange analysis on family energy supply and consumption is shown in the Optimal Home Micro-Grid Energy Management (OHM-GEM) system. By effectively managing power exchange between the microgrid and the



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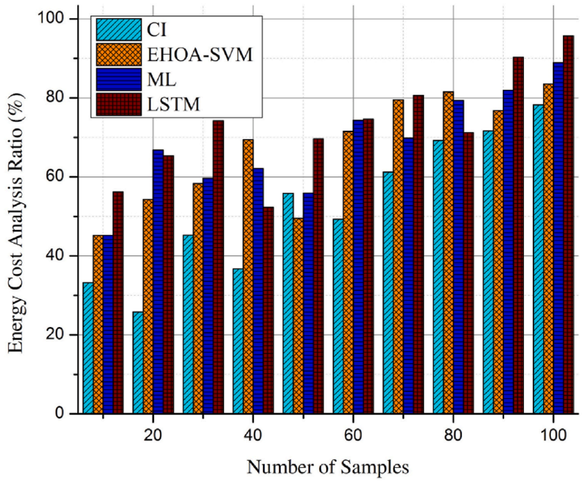


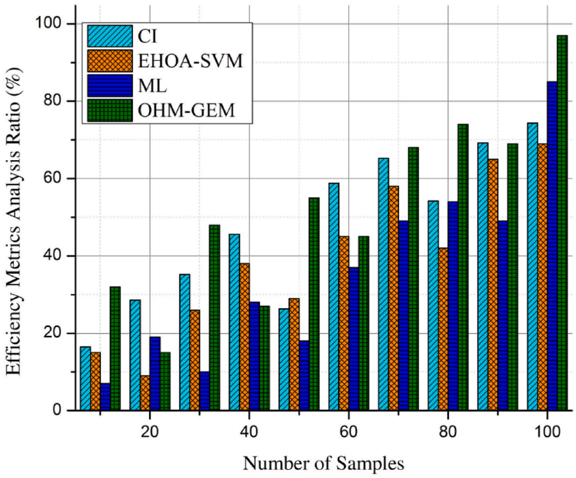
(b)

Fig. 9. (a) - Energy cost analysis is compared with OHM-GEM; (b) -Energy cost Analysis is compared with LSTM.

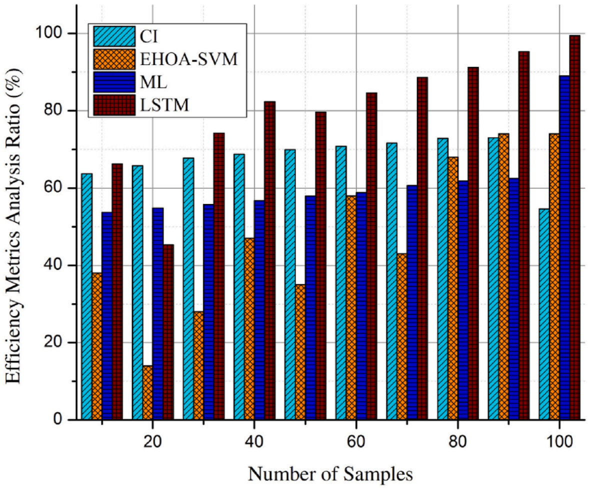
main grid, OHM-GEM offers homes a flexible and reasonably priced energy source. One of OHM-GEM's main characteristics is its capacity to export extra energy during times of abundant generating. The technology returns the extra solar power produced by the microgrid back to the main grid when it creates more than the residence needs, therefore enabling homeowners to get credits or payback. This grid interaction improves financial returns as well as environmental ones.

On the other hand, OHM-GEM allows flawless energy import under poor solar output or great demand. When required, the system automatically moves to grid power to provide a continuous supply of household electricity. Furthermore, OHM-GEM maximizes energy imports employing real-time energy pricing, therefore reducing household expenditures. It automatically reacts to grid circumstances and energy rates, therefore modifying energy consumption patterns to benefit from reduced power costs. This method minimizes energy procurement, therefore lowering power costs. Additionally, by balancing supply and demand, the bidirectional power flow enabled by OHM-GEM helps to maintain grid stability [41,67]. In addition, OHM-GEM and LSTM enable the microgrid to operate in islanded mode during grid disruptions or emergencies, as illustrated in Fig. 11a and b, respectively. By utilizing energy storage and distributed generation, the system maintains power to critical loads, enhancing the resilience and reliability of the household microgrid.

By skilfully controlling the flow of power between the microgrid and the main grid, OHM-GEM lowers costs and maximizes residential energy supplies. This interaction improves home energy efficiency and independence. With a grid power exchange efficiency of 98.4 %, OHM-GEM beats conventional LSTM models with an efficiency of 94.7 %. The sophisticated ability of the system to predict solar power output and optimize energy use gives homes a lower environmental impact, more energy efficiency, and cost savings. Its efficiency is improved even further by smart battery management, flawless grid integration, and condition-oriented adaptation [19,67]. Overall, OHM-GEM is a convincing model for cleaner, more cost-effective home energy management in the future.



(a)



(b)

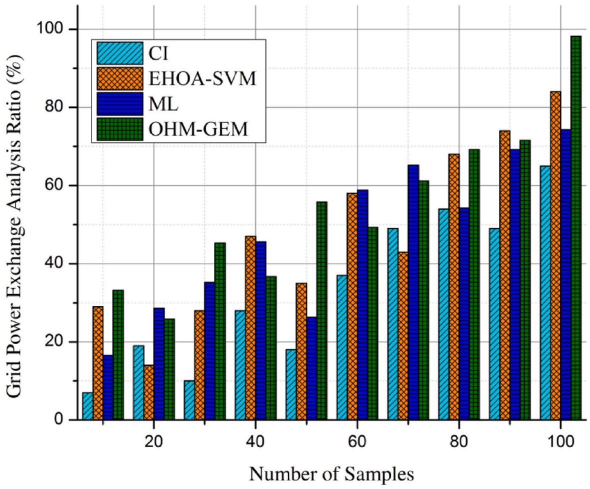
Fig. 10. (a) - Efficiency Metrics Analysis is compared with OHM-GEM; (b) - Efficiency Metrics Analysis is compared with LSTM.

4.6. Mean absolute error, mean square error, and R^2 coefficient

With the system obtaining a mean absolute error (MAE) of 0.5 kWh, Fig. 12a depicts the MAE and indicates robust forecast accuracy in balancing energy supply and demand. Reflecting a low mean squared error (MSE) of 0.35 kWh^2 shows the model's dependability in controlling energy flows, as depicted in Fig. 12b. In Fig. 12c the R^2 coefficient ratios are depicted for all models. An R^2 value of 0.92 indicates that the model is highly predictive, accounting for 92 % of the variability in energy consumption and output. These calculations demonstrate how well the OHM-GEM system promotes sustainability in smart buildings and increases the energy economy.

5. Conclusion

Advancing sustainable energy targets and lowering carbon emissions depend on innovative solar power harvesting techniques being developed. One practical answer is to install photovoltaic (PV) systems in construction. Still unresolved, though, are issues including efficient energy management, different energy needs, and the sporadic character of solar energy. Many times, conventional rule-based systems fall short in handling these complications; thus, fresh ideas are required. This work presents the Optimal Home Micro-Grid Energy Management (OHM-GEM) system based on Enhanced Long Short-Term Memory (LSTM). Designed for household micro-grids featuring PV panels and battery storage, it is Trained with deep learning methods, OHM-GEM takes advantage of an advanced LSTM neural network. This increases the projections of PV power output accuracy. The LSTM network efficiently manages variations in PV output and challenging temporal dependencies. The results of simulations show the system's promise. OHM-GEM lowers costs, improves energy efficiency, and raises dependence on renewable energy sources. This study reveals how deep learning technologies might help to support sustainable energy targets, promoting a more ecologically friendly and energy-efficient future.



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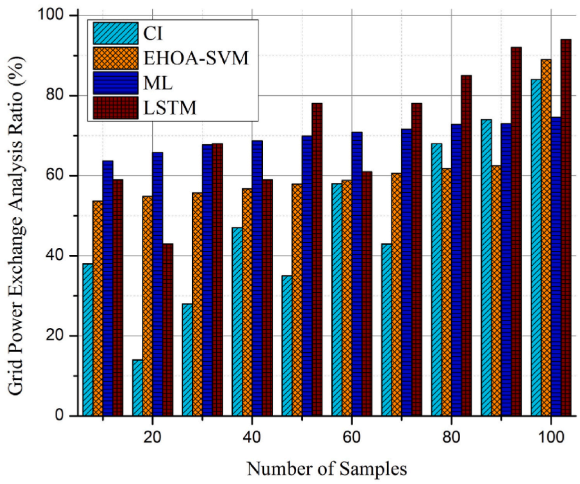

(b)

Fig. 11. (a) - Grid Power Exchange Analysis is compared with OHM-GEM; (b) -Grid Power Exchange Analysis is compared with LSTM.

CRediT authorship contribution statement

Munusamy Arun: Writing – original draft, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Thanh Tuan Le:** Writing – review & editing, Project administration, Conceptualization. **Debabrata Barik:** Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation. **Prabhakar Sharma:** Writing – review & editing, Validation, Supervision, Software, Formal analysis. **Sameh M. Osman:** Writing – review & editing. **Van Kiet Huynh:** Writing – review & editing, Project administration, Conceptualization. **Jerzy Kowalski:** Writing – review & editing. **Van Huong Dong:** Writing – review & editing. **Viet Vinh Le:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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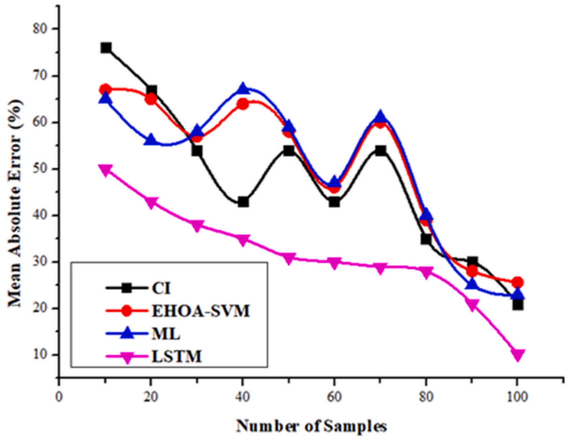

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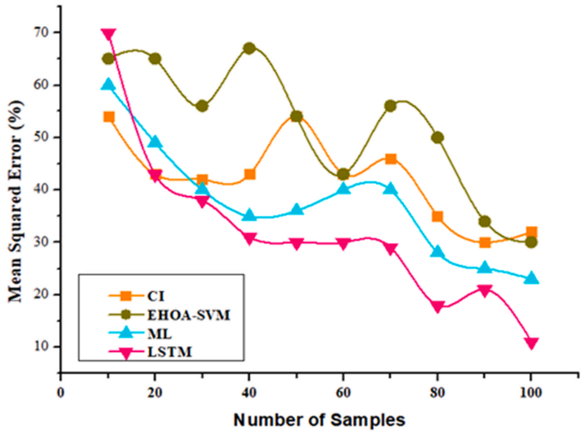

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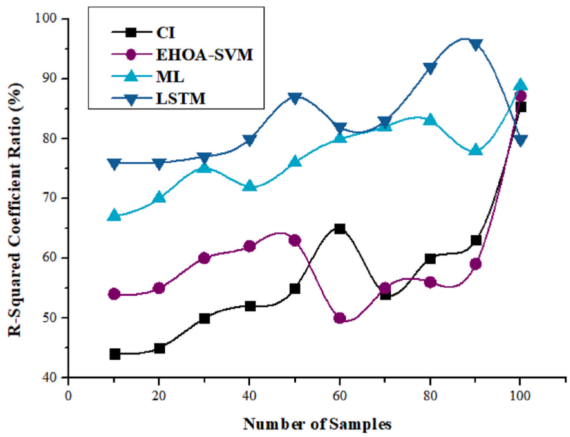

(c)

Fig. 12. (a) MAE, (b) MSE, and (c) R-square coefficient.

Data availability

The data that has been used is confidential.

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