Hybrid Artificial Intelligence Optimization for Solar-Wind Hybrid Energy System Grids

[1]Karthiga M, [2]Saranya K, [3]Sankarananth S

[1,2]Department of CSE, Bannari Amman Institute of Technology, Sathyamangalam, India
[1]karthigam@bitsathy.ac.in, [2]saranyaks@bitsathy.ac.in
[3]Department of ECE, Bannari Amman Institute of Technology, Sathyamangalam, India
sankarananth@bitsathy.ac.in

Abstract:

One potential route to creating reliable and ecological power systems are to integrate energy from renewable resources into intelligent networks. However, the optimal operation of mixed green power sources remains a crucial field requiring in-depth investigation. This work proposes a comprehensive technique that blends AI algorithmic approaches with metaheuristic optimization algorithms to forecast and control sources of clean energy in intelligent grid settings. The suggested HSTM-RL-PPO paradigm outperforms existing models with enhanced [37] precision, recall, and accuracy scores of 0.93, 0.94, and 0.93, correspondingly, in terms of correctly predicting trends in energy consumption. With a success rate of 0.92 on numerous parameters, the TRPO-RL-SA technique is a useful tool for evaluating load balancing. The CNN-PSO technique is particularly actual at forecasting the production of clean energy, with average squared error (MSE), average absolute error (MAE), root average square error (RMSE), R-squared rating, average absolute percentage error (MAPE), and average squared error (RMSE) [37] corresponding to 345.12, 15.07, 0.78, 18.57, and 7.83, respectively. The outcomes of our study contribute to the advancement of hybrid renewable energy sources within intelligent grid systems, leading to enhanced reliability, efficiency, and cost-effectiveness in energy generation and transmission. Additionally, the proposed method appears applicable in remote and off-grid locations. To sum up, our research establishes a valuable framework for enhancing Promoting renewable energy generation, this study acts as a catalyst, encouraging additional exploration into the energy managing domain.

1. INTRODUCTION

The emergence of smart grids has ushered in a revolutionary transformation in energy distribution and management domain. Leveraging cutting-edge sensors, communication technologies, and control systems, these advanced electrical grids are poised to revolutionize energy production, distribution, and consumption [1]. Smart grids play a central role in automating issue detection and determination, thereby elevating reliability, minimizing disruptions in routine operations, and enhancing efficiency. They contribute significantly to energy efficiency by reducing wastages and optimizing utilization of green-energy sources like wind and solar power. The integration of these renewable sources is streamlined, and their inherent variability is effectively managed through optimization processes. The resulting efficiency improvements lead to a reduction in overall electricity costs by diminishing necessity for laying of new transmission cable, plants for generating power, and minimizing energy waste. Intelligent grids also play a vital role in enabling precise control and offering comprehensive insights into consumption patterns, fostering a more sustainable approach to energy usage and potentially lowering energy expenditures for users. In essence, the implementation of smart grids not only saves costs and enhances energy management but also improves the effectiveness, consistency, and sustainability of electricity scheme.

The ascent of the InternetofThings (IoT) has arisen as a fundamental factor in current transformative phase, amplifying the importance of deploying intelligent grids in recent times. Real-time data collection and analysis from diverse sources within an intelligent grid are now feasible, thanks in large part to IoT devices and methodologies. IoT plays a crucial role in smart grids in several important ways. [4,5]:

- *Real-time tracking:* Important characteristics like electrical performance and usage can be tracked in real time by devices connected to InternetofThings, or IoT. The reliability of the grid was ensured by the timely detection and resolution of issues, which is made possible by the real-time data.
- *Sophisticated statistics:* Devices and platforms within the Internet of Things have the capability to conduct advanced analytics, streamlining the analysis of extensive datasets from various sources, including meter readers and sensors. This analytical capability can be employed for intelligent network optimization in areas such as energy generation, transportation, and utilization.
- *Predictive maintenance:* Through the utilization of Internet of Things (IoT) devices, utility companies can implement proactive maintenance strategies for the electrical grid. This enables them to pinpoint and act on potential concerns before they escalate into breakdowns or some other complications.
- *Demand-responsive*: The success of demand-side management programs hinges on the integration of IoT devices and platforms. These initiatives actively encourage the use of sustainable energy sources, mitigate demand spikes, and improve overall grid

efficiency by incentivizing customers to reduce energy consumption during peak periods.

- *Integration of distributed electrical assets:* The role of IoT devices is crucial in facilitating the seamless incorporation of dispersed power assets, such as solarpanels and windmills, into grid. These solutions act as a key role in effectively dealing the variability of these assets, ensuring their optimal utilization, especially in scenarios where integration may present challenges [6].

The InternetOfThings (IoT) assumes significant role in advancement and maneuver of intelligent grids, highlighted by its capabilities in up-to-the-minute monitoring, insightful analytics, proactive maintenance, and support for peak demand management. Moreover, IoT ensures the smooth integration of various energy sources, making a substantial contribution to optimizing the grid's performance and overall effectiveness. The practical incorporation of various sustainable energy sources within the broader framework of power systems is made possible by Hybrid Renewable Energy Systems (HRES), providing intelligent grids with a constant and consistent power supply. The integration of these elements brings forth numerous benefits, including heightened dependability, increased productivity, enhanced adaptability, improved affordability, and a positive ecological impact. Looking to the future, HRES ensures a steady and reliable power supply by optimizing energy ex raction and minimizing waste. The remaining research will examine the AI exploitation and optimization approaches to boost effectiveness of hybrid green energy sources and show how they can radically change how environmentally friendly energy is produced and used.

These are the sections that make up this document. We give a comprehensive review of current studies on the suggested topic in Section 2. This section reviews a few earlier studies and approaches, outlining the benefits and drawbacks of each. We discuss the approaches used in this investigation to attain the anticipated outcomes in Section 3. We present an in-depth explanation of the CNN-PSO technique, the TRPO-RL-SA methodology, and the Hybrid STM-RL with Proximal Policy Optimization (PPO) system, along with the steps taken for implementation and evaluation. Section 4 furnishes a comparative analysis of the results, juxtaposed with previous research on the topic. An exhaustive assessment of the suggested models' effectiveness and methodologies in contrast to earlier techniques provides insightful perspectives on their superiority and effectiveness. Moving on to Section 5, it offers an all-encompassing overview of the research, accentuating pivotal findings and contributions. This section elucidates potential implications, explores broader ramifications, and puts forth recommendations for future research directions.

2. RELATED WORK

Various methodologies have been devised to enhance the efficiency of IoT-driven intelligent grids, concentrating on aspects such as connectivity, energy conservation, and electrical power. The presented paper [1] delves into a diverse array of solutions, encompassing demand response, predictive maintenance, real-time monitoring, data analytics, seamless integration of clean energy sources, and cybersecurity concerns. The document underscores the advantages of these varied strategies while acknowledging the challenges associated with their implementation, providing valuable insights for forthcoming examination in this swiftly budding domain.

The central theme of this discourse revolves around optimizing the amalgamation of Big Data analytics and Internet of Things (IoT)[37] technology with renewable energy sources. A focal point highlighted in the discussion is the facilitation of demand response programs in seamlessly incorporating renewable energy sources through the promotion of timely monitoring and effective electricity usage management. Emphasizing the construction of Demand Response Programs, the discussion underscores their role in enhancing grid efficiency and flexibility [2]. The paper systematically addresses the identification of integration challenges associated with this concept, unraveling the complexities involved. Beyond the delineation of issues, the paper extends its scope to propose future research directions that have the potential to address these challenges comprehensively and successfully. The imperative for a thoughtful and balanced approach to the rapidly evolving field of smart grid technology is accentuated by the attention given to both the benefits and challenges inherent in integrating renewable energy through IoT and Big Data Analytics.

[3] proposes a research focus on the strategic integration of diverse renewable sources and loading facilities to develop hybrid renewable energy systems. Recognizing sporadic nature of greenenergy, this holistic approach aims to enhance overall grid performance. By conducting a thorough analysis of the challenges and advantages inherent in these hybrid

systems, the investigation offers significant revelations into promising avenues for prospective studies and development in this domain.

The review within this context centers on the accomplishments of IoT-powered intelligent grids. The suggested practices, encompassing robust cybersecurity, real-time energy consumption monitoring and control, seamless integration of renewable sources, implementation of Demand Response Programs, and optimization of big data and machine learning, are implemented and scrutinized [4]. This thorough analysis offers a nuanced understanding of the challenges faced by IoT-powered smart grid systems, highlighting both successes and obstacles. The paper comprehensively assesses the advantages and difficulties experienced by intelligent grid devices, systematically addressing areas related to IoT that require further research and development [5]. Additionally, the study broadens its scope to conduct a thorough examination of IoT technology application in smart grids, emphasizing the resolution of implementation challenges.

The research [6] presents a collection of methods for executing Energy Management Agent Frameworks (EMAFs) in 5G vertical companies. Leveraging multi-agent platforms, these techniques enable coordination and communication among heterogeneous systems and devices, yielding adaptable and scalable frameworks suitable for a broad spectrum of applications. The study emphasizes the crucial role EMAFs play in 5G wireless networks for immediate use tracking and management, describing potential benefits and challenges that warrant further investigation and advancement.

Similarly, [7] introduces an innovative demand-response technique for scaling hybrid energy systems (HESs), enhancing end-user energization, and maximizing web performance. The learning mentions employing sophisticated control algorithms, including prediction models, to ensure consistency and robustness of energy source. It proposes modeling approach to calculate the appropriate capacity of hydrogenenergy storagesystem, carefully weighing possible benefits and drawbacks and offering opportunities for further investigation and improvement.

On a different note, [8] advocates for creating a standalone Hybrid Renewable Energy System (HRES) specifically tailored for a Saudi enterprise. Employing battery storage and solar or wind power sources, this system aims to deliver a consistent and dependable power supply. The study evaluates feasibility and economic viability through technical analysis, emphasizing the implementation of advanced monitoring and management systems to maximize performance. It addresses challenges associated with HRES implementation and asserts the potential for significant financial gains, improved energy efficiency, and reduced carbon emissions.

Additionally, [9] suggests integrating renewable energy sources, particularly wind and solar power, to maximize energy source resizing and improve electricity distribution in an island microgrid located on a hydrocarbon platform in Tunisia. The study proposes a tiered control system for an effective energy distribution plan, aiming to ensure reliability across various load conditions and optimize the cost and efficiency of microgrids.

[10] aims to conduct a thorough sensitivity and economic study of a Hybrid Renewable Energy System (HRES). Utilizing a Monte Carlo simulation technique, the study evaluates economic viability and sensitivity to various input parameters and uncertainties. It recommends a techno-economic analysis methodology considering return periods, operating costs, capital expenditures, and energy gains. The research highlights the use of an optimization model to determine the ideal weight and arrangement of HRES components for maximizing financial benefits.

In summary, these collaborative efforts exemplify comprehensive approaches to address energy-related challenges in microgrids. They propose innovative solutions incorporating modern management systems, optimization models, renewable energy sources, and financial viability analyses.

2.1 Identification of Research Gap

A meticulous examination of the literature on Internet of Things (IoT)-based smart grid systems [14] and hybrid renewable energy systems [15] has unveiled significant research gaps. To bridge these gaps, this study pioneers an approach by integrating three essential techniques—power response, load management, and consumption forecasting—within the framework of the Intelligent Electricity System. What distinguishes this contribution is its demonstration of the advantageous outcomes resulting from the combined application of these strategies, previously explored independently in prior research. The primary aim is to address the identified research gaps through the utilization of smart grid technologies, IoT, and hybrid renewable energy systems [16].

The central focus of this research revolves around optimizing hybrid renewable energy systems, a pivotal aspect for ensuring dependable, cost-effective, and efficient energy production and distribution within smart grids [17–19]. To achieve this optimization, diverse strategies such as demand response, battery storage, load distribution, and precise energy source predictions are employed. The efficacy of these approaches is further enhanced by advanced analytics and data management technologies, extensively elaborated in the subsequent sections [20].

The overarching goal is to establish an environment that maximizes the production and distribution of energy in an efficient and sustainable manner. The implementation of these well-considered concepts aims to ensure a continuous and dependable energy supply. The proposed paradigm advocates for synthesis of artificial intelligence (AI) approaches with fine-tuning approaches. This integration seeks to manage demand response, renewable energy forecasting, and load balancing effectively, creating a comprehensive and cutting-edge system [21–23]. This approach underscores the importance of an integrated and intelligent system, recognizing the interdependence of different elements to address challenges entwined with optimizing hybrid greenenergy sources within an intelligent grid environment.

3. **MATERIALS AND METHODS**

The seamless coordination of renewable energy forecasting, load balancing, and demand response within hybrid renewable energy systems in smart grid contexts relies on the integration of Artificial Intelligence (AI) techniques with optimization algorithms [20].

Demand Response:

An innovative approach to demand response management is introduced, combining Reinforcement Learning Proximal Policy Optimization (RSLO) with Hybrid Short-Term Memory (HSTM-RL-PPO). This advanced technique focuses on predicting energy consumption trends and identifying opportunities for demand response. Using diverse datasets, including energy usage trends and meteorological information, HSTM-RL-PPO identifies windows for reduction and spikes in demand. Optimization algorithms are then applied to formulate dynamic demand response management strategies, potentially prioritizing responses based on energy costs or renewable energy source availability [21].

Load Balancing:

Reinforcement learning acts as an AI method to enhance load balancing in hybrid renewable energy systems [22]. This involves generating solutions for distributing energy loads among various sources by closely analyzing patterns of energy production and consumption. Metaheuristic optimization algorithms continually refine these techniques in response to shifts in energyproduction and utilization trends.

Clean Energy Forecasting:

Artificial Intelligence technologies, including neural networks and decision trees, demonstrate effectiveness in forecasting renewable energy [23]. These methods predict energy production from renewable sources by incorporating data on past electricity creation and weather trends. Metaheuristic optimiz-ation methods are then applied to manage the production of greenenergy based on outlooks. This approach is commonly employed in energystorage systems to stockpile excess greenenergy during peak periods and ensure a balanced supply and demand during periods of decreased output.

This holistic solution specifically addresses load balancing, renewable energy predictions, and demand response, emphasizing the crucial role of optimization algorithms and AI techniques in realm of hybrid greenenergy systems operating in smart grid environments.

The proposed strategy combines artificial intelligence methods with metaheuristic optimization algorithms, offering a novel method to boost the consistency and efficiency of hybrid greenenergy systems in smart grid scenarios. A hybrid strategy employing TRPO-RL-SA, HSTM-RL-PPO, and CNN-PSO approaches is adopted for foretelling and controlling greenenergy generation. The comprehensive strategy unfolds in three steps:

Step 1: Data Collection and Preprocessing:

Relevant data on past energy use, weather trends, and pertinent variables are gathered and pre-proces-sed to ensure accuracy and suitability for subsequent model usage.

Step 2: Training and Optimization:

Advanced AI algorithms, including HSTM-RL-PPO for energy use pattern prediction and TRPO-RL-SA for load balancing, are applied. The CNN-PSO approach optimally predicts renewable energy output. Solutions are crafted to effectively manage anticipated renewable energy output.

Step 3: Implementation and Monitoring:

The finalized strategies are incorporated into the energy framework, accompanied by a robust monitoring system to continually evaluate system performance. Dynamic monitoring allows for timely adjustments to achieve optimal efficiency.

By amalgamating HSTM-RL-PPO, TRPO-RL-SA, and CNN-PSO appraoches, proposed solute-ion offers an inclusive and effective approach to handle the involved tasks related with predicting and managing renewable energy generation. These interdependent techniques create a robust framework, as illustrated in Figure 1, enabling hybrid renewable energy systems to function optimally and intelligently in the dynamic context of smart grid environments.

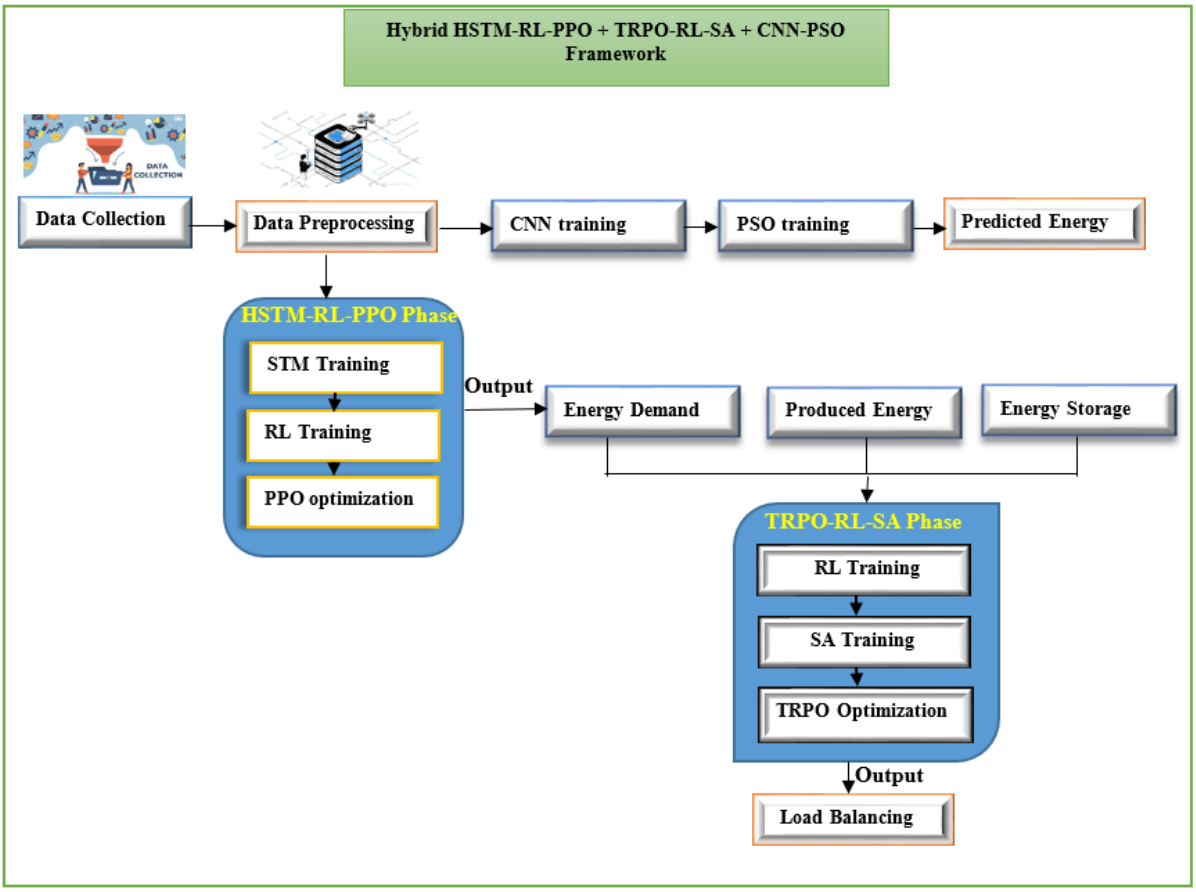


Fig 1. Architecture for Hybrid HSTM-RL-PPO + TRPO-RL-SA + CNN-PSO for Smart Grids

3.1 Forecasting Demand Reaction Using the HSTM-RL-PPO Algorithm

In the ever-evolving landscape of energy consumption patterns, the Hybrid Short-Term Memory, and Reinforcement Learning with Proximal Policy Optimization (HSTM-RL-PPO) algorithm emerges as a valuable tool for forecasting demand response dynamics. The Hybrid Short-Term Memory (HSTM) neural network, an enhanced iteration of the Long

Short-Term Memory (LSTM) neural network [25], proves instrumental in analyzing sequential data, particularly time series data related to energy consumption patterns. The HSTM component's proficiency in recognizing historical energy consumption patterns enables precise projections of future energy usage. However, to ensure the generation of cost-effective and efficient demand response plans, Reinforcement Learning (RL) algorithms [26] are incorporated due to the occasional limitations of the autonomous HSTM.

Reinforcement learning algorithms operate within a learning domain primarily focused on reward or penalty systems, employing a trial-and-error methodology. The HSTM-RL-PPO algorithm synergistically combines the strengths of HSTM and RL techniquesIn response to predictions generated by the Hybrid Short-Term Memory (HSTM) component concerning energy consumption patterns, the Reinforcement Learning (RL) counterpart optimizes demand response tactics.

During the training phase, an extensive dataset, including historical energy usage trends, meteorological data, and other relevant factors, is input into the HSTM-RL-PPO algorithm. The RL component utilizes insights from HSTM forecasts to make judgments about demand response strategies, while the HSTM component learns and predicts patterns in energy usage over time. For instance, incorporating contributions such as weather anticipation and energy expenditure trends, the HSTM-RL-PPO algorithm excels in anticipating peak demand times and identifying opportunities for reduction. These forecasts contribute to the creation of intelligent demand response strategies, including temperature control, scheduling energy utilization for slack hours, or judicious use of energystorage systems. Ultimately, reinforcement learning module refines these strategies through feedback, identifying the most effective approaches.

The integration of the HSTM and RL approaches in the HSTM-RL-PPO algorithm yields a potent and adaptable tool for demand response optimization in hybrid renewable energy systems, enhancing efficiency and economy of scale by providing accurate predictions of energy consumption trends and facilitating optimal decision-making.

Algorithm: Hybrid STM-RL

Step 1: Data Collection

Compile historical information on energy expenditure, climate information, and added pertinent factors.

Step 2: Data Pre-processing

Complete necessary pre-processing procedures to make collected data usable for the HSTM-RL-PPO model.

Step 3: HSTM Model Training

Train the HSTM model with pre-processed data for precise forecasting of patterns in energy usage.

Step 4: RL Model Training

Utilize insights from HSTM projections to optimize demand response strategies in the RL model.

Step 5: Integration of HSTM and RL Models

Combine trained RL and HSTM models to create a cohesive hybrid model.

Step 6: Model Deployment

In a concurrent smart-grid situation, use hybrid HSTM-RL-PPO model to estimate energy consumption patterns and enhance demand response strategies promptly.

Step 7: Monitoring and Model Updating

Continuously monitor real-time performance of the hybrid HSTM-RL-PPO model.

Update the model as needed to ensure optimal performance and responsiveness to changing grid conditions.

3.2 Utilizing RL and HSTM to Optimize Demand Response

The combination of Hybrid Short-Term Memory (HSTM) and Reinforcement Learning with Proximal Policy Optimization (PPO) in the HSTM-RL-PPO framework presents a robust strategy to enhance demand responsiveness within the dynamic domain of energy consumption patterns.

The HSTM, an advanced iteration of the LongShortTermMemory (LSTM), elevates as a distinctive variant of a RecurrentNeuralNetwork tailored for analyzing sequential data, particularly historical energy usage data. Its primary purpose is to predict demand patterns, particularly when demand response is a factor. The HSTM layer processes sequential input data through various gates, including input, output, forget, and memory gates. Each gate plays a pivotal role in recognizing patterns, selecting significant inputdata for retention, preventing information overwork with unnecessary data, and utilizing deposited data for predictive purposes. Leveraging output of HSTM layer, the subsequent layer predicts the energy demand.

The following are the mathematical representations of the various levels:

1. Input Gate(i_t):
   - $i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i$ [1]
2. ForgetGate(f_t):
   - $f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f$ [2]
3. Output Gate(o_t):
   - $o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o$ [3]
4. Candidate's Memory Cell($\breve{C}_t$):
   - $\breve{C}_t = \tanh(W_c.\left[h_{t-1,} x_t\right] + b_c$ [4]
5. Memory Cell(C_t):
   - $C_t = f_t.C_{t-1} + i_t * \check{C}_t$ [5]
6. Hidden State(h_t):
   - $h_t = o_t * \tanh(C_t)$ [6]

Where:

- W_i, W_f, W_o, and W_c show weight matrices connected to the corresponding gates.
- σ symbolizes the activation function of the sigmoid.
- *tanh* is hyperbolic activationfunction of tangent.
- $\left[h_{t-1,} x_t\right]$ symbolizes the union of current input $h_{t-1,}$ and with prior hiddenstate $x_{\ t}$
- $b_{i\ ,}\ b_t, b_o, b_c$ are bias vectors for the corresponding gates.

By fine-tuning parameters during training, HSTM network predictions enable more precise optimization of mandate response approaches, such as fine-tuning energy consumption in response to varying request circumstances. The process of reinforcement learning starts with environment initialization. This includes system's present state, projected energy consumption, and the energystorage situation. The next step is to characterize the action space, which includes possible actions like changing the temperature or using energystorage. A reward system is established to encourage ideal behavior by discouraging excessive consumption and the dependence on nonrenewable energysources, while incentivizing lower ingesting during highdemand periods and use of greenenergy sources. Through continuous refinement with new data inputs, Reinforcement Learning (RL) algorithm ultimately executes optimal demandresponse scheme. This ensures the implementation of effective demand response programs, fostering a reduction in usage of nonrenewable energysources.

A crucial component in this process is ProximalPolicyOptimization (PPO) method. PPO plays vital role in enhancing demand forecast accuracy, thereby improving the overall effectiveness of the hybrid algorithm. With pre-processed data, a Hybrid ShortTermMemory (HSTM) neuralnetwork is trained to accurately detect past trends in energy usage and predict future demand patterns. RL algorithms leverage the predictions from the HSTM neural network to optimize demand response techniques. Achieving this involves building a system that rewards effective and efficient demand response, using trial-and-error methods to regulate optimal course of action.

The application of Proximal PolicyOptimization (PPO) technique further enhances the optimization process. PPO focuses on adapting policy parameters to ensure consistent and continual learning throughout the Reinforcement Learning (RL) optimization phase, maintaining a delicate balance between exploration and exploitation. By carefully adjusting policy parameters, PPO ensures that incentives for optimal performance are appropriately aligned, contributing to the improvement of the reward function. This involves promoting the use of renewable energy sources, discouraging excessive reliance on non-renewable sources, and offering incentives for reduced usage during periods of high demand.

The hybrid algorithm, incorporating RL, PPO, and HSTM, undergoes continuous learning and updating. As new data inputs become available, the PPO approach dynamically adjusts and refines policy parameters, optimizing demand forecasting and response tactics.The best demand response plans that resulted from HSTM, RL, and PPO working together are put into action at the end of the process. Thus, in dynamic energy circumstances, effective and flexible demand forecasting and response are guaranteed.

3.3 Optimizing Load Distribution using the Suggested TRPO-RL-SA Algorithm for Effective Results

To attain well-organized loadbalancing in a hybrid greenenergy system, the following steps are employed through the utilization of the proposed Trust Region Policy Optimization with Reinforcement Learning and Simulated Annealing (TRPO-RL-SA) algorithm:

- Data Collection on Energy Production and Consumption Patterns: First information is obtained about the energy production and consumption patterns of all the sources in the structure, which include conventional, wind, and solar energy. [27].
- Initial Load Balancing Strategies Using Reinforcement Learning (RL) Techniques: Initially, load balancing strategies are developed using RL approaches. These approaches consider the energy storage systems' capacities, the energy production that is occurring right now, and the anticipated energy demand.
- Integration of Trust Region Policy Optimization (TRPO) and Simulated Annealing (SA): The TRPO-RL-SA algorithm is introduced to further enhance the load balancing strategies developed through RL. TRPO ensures constant policy updates, whereas SA, a metaheuristic optimization technique [28], refines these strategies to identify the optimal load balancing configurations. The aim is to augment the employment of sustainable energysources while minimizing reliance on non-sustainable energy sources.
- Continuously gather new data and closely monitor the effectiveness of the system's load balancing. Implement improved load balancing strategies derived from the TRPO-RL-SA algorithm.
- Ensure the adaptability of load balancing solutions by regularly updating the Reinforcement Learning (RL) agent with relevant inputs. Make adjustments to electricity creation and ingestion to guarantee the competent utilization of all accessible energysources.
- The proposed Trust Region Policy Optimization with Reinforcement Learning and Simulated Annealing (TRPO-RL-SA) algorithm provides a sophisticated and flexible approach to achieving effective load balancing in hybrid

greenenergy systems within a smartgrid environment. This algorithmic framework is designed to maximize the utilization of greenenergy sources and minimize reliance on nonrenewable energysources, optimizing load distribution for efficient and sustainable energy management.

Algorithm: Hybrid TRPO-RL-SA

```
def perform_optimized_load_balancing(data):
    # Step 1: Initialize the Trust Region Policy Optimization with Reinforcement Learning agent
        trpo_rl_agent = create_trpo_rl_agent(data)
    # Step 2: Train the TRPO-RL agent
        trpo_rl_agent.train_agent()
    # Step 3: Initialize the Simulated Annealing algorithm
        annealer = initialize_simulated_annealing()
    # Step 4: Optimize the load balancing strategies using TRPO-RL
    optimized_strategies = annealer.optimize_strategies(trpo_rl_agent.get_current_strategies())
    # Step 5: Implement the optimized load balancing strategies
        implement_optimized_strategies(optimized_strategies)
    return optimized_strategies
def create_trpo_rl_agent(data):
    # Implementation of TRPO-RL agent initialization based on input data
    trpo_rl_agent = TRPOReinforcementLearningAgent(data)
    return trpo_rl_agent
def initialize_simulated_annealing():
    # Implementation of Simulated Annealing algorithm initialization
        annealer = SimulatedAnnealingAlgorithm()
    return annealer
```

```
def implement_optimized_strategies(optimized_strategies):
    # Implementation of applying the optimized load balancing strategies
        for strategy in optimized_strategies:
            strategy.apply()
```

The process begins by establishing a reinforcement learning agent trained on available data. With a focus on maximizing benefits, this agent is trained to execute actions that encourage the utilization of renewable energy. Subsequently, the Trust Region Policy Optimization with Reinforcement Learning and Simulated Annealing (TRPO-RL-SA) technique is incorporated into the algorithm. Leveraging insights from the agent, the TRPO-RL-SA algorithm optimizes load balancing strategies to identify optimal solutions while enhancing exploitation of greenenergy sources. As algorithm implements these optimal load balancing strategies by managing energy requirements and fine-tuning greenenergy sources generation, emphasis is on transitioning towards more sustainable and renewable energy methods.

3.4 RenewableEnergy Production Forecasting with Suggested CNN-POSO

1. To effectively predict and control the generation of renewable energy, the ConvolutionalNeuralNetwork-ParticleSwarmOptimization (CNN-PSO) technique can be applied through the following steps:
2. Gather data on relevant variables, including historical energy output and weather patterns, influencing the production of renewable energy.
3. Develop models using a ConvolutionalNeuralNetwork (CNN) to foresee greenenergy production based on identified factors.
4. Utilize ParticleSwarmOptimization (PSO), a metaheuristic finetuning technique, to fine-tune strategies for managing renewable energy production based on the generated predictions.
5. Incorporate energy storagetechnologies, such as batteries or pumped hydrostorage, to store leftover greenenergy during high demand.
6. To ensure flexibility in response to changing conditions, continuously monitor system performance, acquire fresh data, and update models and administration strategies completed time.
7. Device the best practices for management the energy system's renewable energy output.

Through the implementation of these all-encompassing methods, the suggested course of action guarantees efficient management of renewable energy generation, promoting a steady and dependable energy source and falling dependency on nonrenewable energysources.

4.RESULTS AND DISCUSSION

The "Smart Meter Power Consumption Data in London Households [11]" dataset, collected from UK Power Networks and made public by London Data store News, is used in this study. To enhance the dataset, further data from the DarkskyAPI and Acorndata from ConsolidatedAnalysisCenter, Incorporated (CACI) were added using a modified type of Kaggle data. Categorical data from Darksky API was subsequently excluded, resulting in the dataset illustrated in Figure 2.

```
time,visibility,windBearing,temperature,dewPoint,pressure,apparentTemperature,windSpeed,humidity,KWH/h
2011-12-11 00:00:00,12.5,210,2.83,1.17,1015.67,1.11,1.78,0.89,101.01700030000003
2011-12-11 01:00:00,12.65,204,2.48,0.81,1014.96,0.31,2.11,0.89,89.84999999999995
2011-12-11 02:00:00,13.02,214,2.7,1.29,1014.42,0.11,2.57,0.9,70.017
2011-12-11 03:00:00,13.05,211,3.47,1.41,1013.78,0.66,3.0,0.86,63.48800010000002
2011-12-11 04:00:00,12.97,204,3.74,1.53,1012.94,1.29,2.64,0.85,56.196
2011-12-11 05:00:00,12.68,201,4.23,2.48,1012.42,1.82,2.7,0.88,59.9299999
2011-12-11 06:00:00,12.54,199,5.16,3.01,1011.74,3.03,2.57,0.86,67.3560001
2011-12-11 07:00:00,12.5,198,4.98,3.13,1011.26,2.39,3.12,0.88,67.66100019999999
2011-12-11 08:00:00,12.01,190,5.79,3.73,1010.85,3.13,3.48,0.87,84.3929999
2011-12-11 09:00:00,12.57,194,6.43,4.85,1010.44,3.72,3.79,0.9,111.02000010000005
2011-12-11 10:00:00,12.54,195,7.05,5.44,1009.82,4.1,4.55,0.9,116.5149998
2011-12-11 11:00:00,12.73,197,7.97,6.02,1009.13,4.95,5.23,0.88,120.6340003
2011-12-11 12:00:00,11.7,197,8.06,6.04,1007.99,4.78,6.02,0.87,148.44800000000004
2011-12-11 13:00:00,13.16,194,8.56,5.92,1006.74,5.44,5.9,0.83,148.6960006000001
```

Fig 2. Dataset preview

Some data points were removed in order to improve understanding of power consumption patterns because they did not significantly correlate with usage points. The data points that were removed included the precipitType, icon, and weather summary. Instead, new criteria were created by categorizing pre-existing data including humidity, wind force, direction, and apparent temperature. These categorical variables were useful for preliminary analysis of the data utilized in the STM, even if they were not used for predictive mining. The dataset's key features for forecasting demand response are energy consumption, meteorological information, time specifics, seasonality (e.g., temperature fluctuations), and energy sources. Other features are eliminated from the dataset and the current features are used.

4.1 Anticipating Demand Response

A new model called hybrid STM-RL-PPO makes it easier to anticipate and control energy use during peak usage, or demand response. This model incorporates a comprehensive set of data, encompassing historical energy consumption statistics, building attributes, occupancy rates, and weather patterns. These attributes serve as essential inputs for the model, enabling accurate predictions of future energy usage and real-time optimization of demand response strategies. For example, the model can guide consumers to diminish energy custom throughout epochs of high demand or assist them in adapting their energy consumption during peak demand intervals. These attributes of the model enable the formulation of more efficient demand response strategies, leading to a significant decrease in overall expenditure of energy during peak demands. To guarantee ideal performance of model and enhance precision of demand response predictions, it is indispensable to gather and analyze applicable data from diverse sources.

In addition to utilizing the "Smart Meter Power Consumption Data in London Households," the study incorporates various other datasets, including the "Smart Building System" and "Hourly Energy Demand Generation and Weather" datasets from Kaggle [11] and Kaggle [12]. Each dataset undergoes thorough examination, and a synthetic sampledataset is generated for investigation. This dataset encompasses variables such as historic energy usage data, climate information, building appearances, tenancy details, time specifications, seasonality, and energy sources. For study, a trial dataset containing 500 records is created, and Table 1 provides a concise overview of the amalgamated data from all datasets.

Table 1. Sample of the dataset utilized for the study

Energy Consumption	Weather Temperature (F)	Building Size (sq. ft.)	Number of Occupants	Weather Condition	Time of Day	Season	Energy Source
125	67	1500	2	Sunny	8:00 AM	Spring	Electric
143	72	2000	3	Cloudy	9:00 AM	Spring	Natural Gas
168	80	2500	4	Rainy	11:00 AM	Summer	Solar
180	82	3000	5	Sunny	1:00 PM	Summer	Wind
195	77	1800	2	Cloudy	3:00 PM	Fall	Electric
205	72	2200	3	Rainy	5:00 PM	Fall	Natural Gas
180	65	2800	4	Sunny	6:00 PM	Winter	Solar

165	60	1800	2	Cloudy	7:00 PM	Winter	Wind
150	55	2000	3	Rainy	9:00 PM	Spring	Electric
135	50	2500	4	Sunny	11:00 PM	Spring	Natural Gas

The [37] accuracy, precision, and recall values that the proposed HSTM-RL-PPO model achieved are shown in Figure 3. According to the data, the recommended model outperforms strategies employing Linear Regression [30], Random Forest [31], SVM [32], Neural Networks [33], and LSTM by 28%, 15%, 22%, 10%, and 6%, in terms of accuracy. In terms of precision [37], the suggestedmodel performs better than LSTM, Random Forest, SVM, Linear Regression, and Neural Networks by 23%, 14%, 20%, 10%, and 6%, respectively. In addition, the recall values of the suggested model show increase over LinearRegression, RandomForest, SVM, NeuralNetworks, and LSTM approaches of 24%, 15%, 22%, 9%, and 5%, respectively.

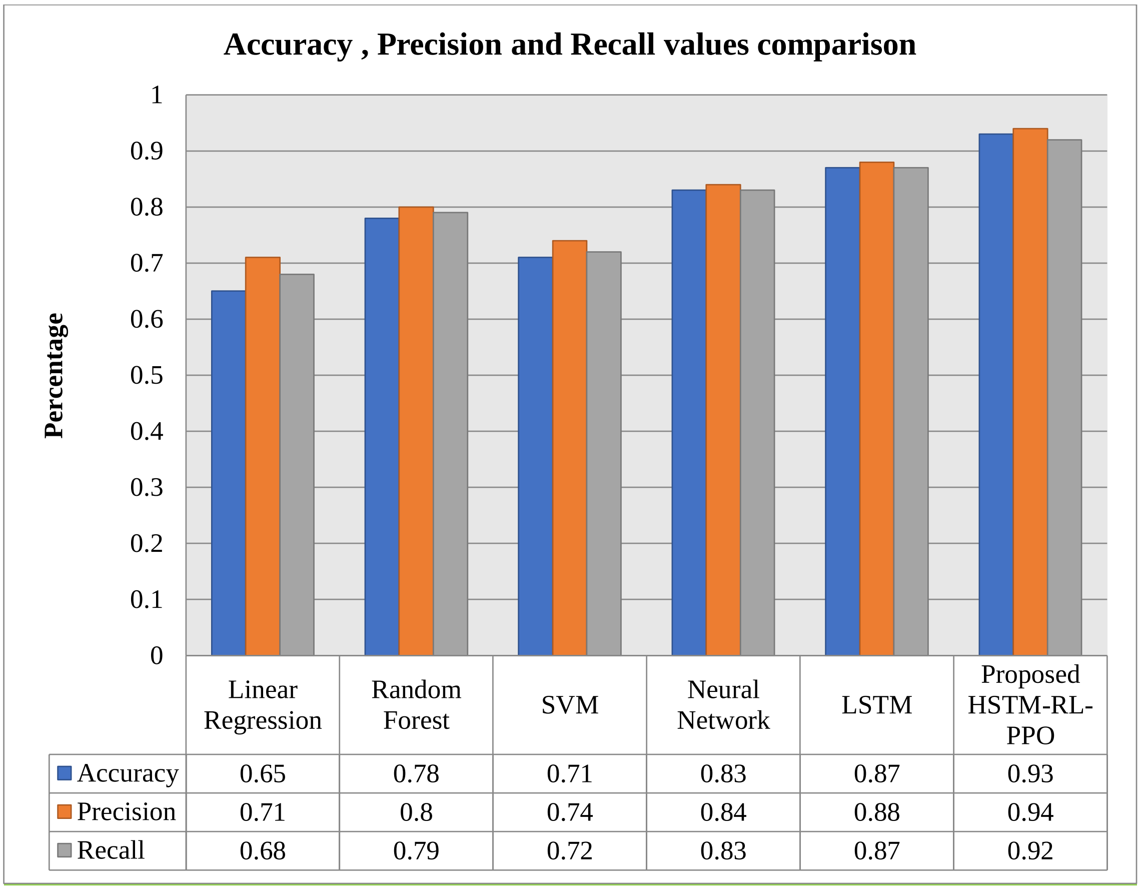
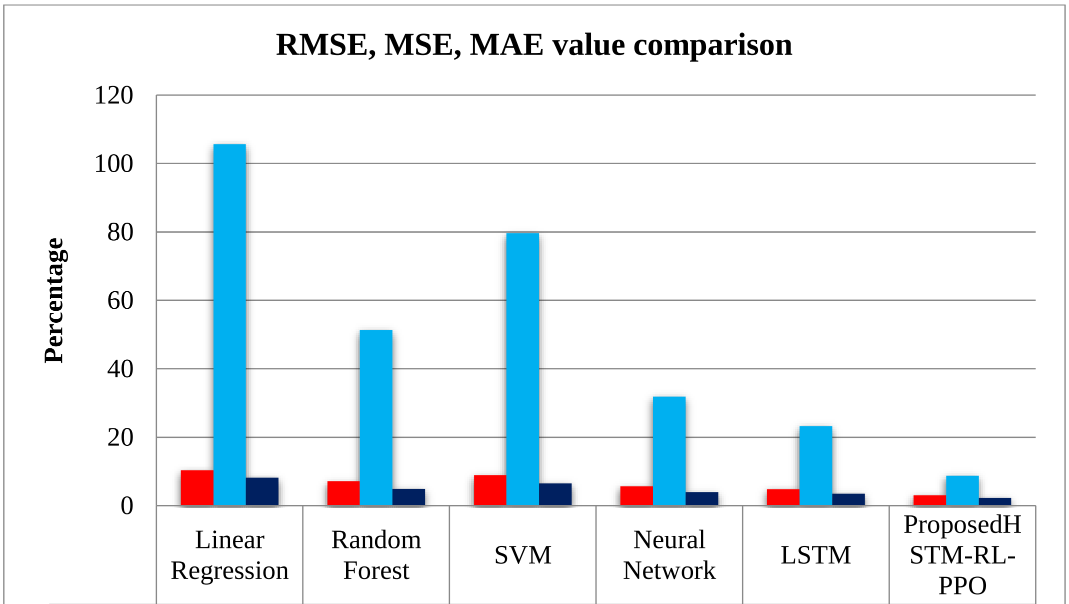


Fig 3. Precision, Recall and Accuracy values comparison of the proposed HSTM-RL-PPO with existing techniques

A evaluation of the proposed HSTM-RL-PPO for demand response prediction is shown in more detail in Figure 4. The recital of the model is appraised using a few commonly used metrics, such as Mean Squared Error (MSE) [33], Root Mean Squared Error (RMSE) [33], and Mean Absolute Error (MAE) [33]. By quantifying the disparities between anticipated and actual values, these metrics indicate accuracy of model in its estimates. Lower levels of these measurements correspond to reduced errors, signifying that model's estimates thoroughly bring into line with real-world data. The suitable range for these metrics can vary based on definite problem and application requirements. The propos-ed model demonstrates superior performance related to other prevailing algorithms, as illustrated in Figure 4, with low RMSE values of 2.98, MSE values of 8.78, and MAE values of 2.28. The data analysis indicates that the HSTM-RL-PPO strategy outperforms traditional machine learning techniques across various metrics, including recall, accuracy, precision, RMSE, MSE, and MAE[37]. This suggests that HSTM-RL-PPO algorithm stands out as the most effective approach for demandesponse prediction and optimization stratagems. Leveraging model's exceptional accuracy and precision, significant reductions in energy consumption during peak demand hours can be achieved, leading to potential cost savings and increased energy efficiency. Figure 5 visually represents the accuracy and loss trends of the model over ten training epochs.



	Linear Regression	Random Forest	SVM	Neural Network	LSTM	ProposedHSTM-RL-PPO
RMSE	10.28	7.16	8.92	5.64	4.82	2.98
MSE	105.61	51.29	79.62	31.85	23.24	8.78
MAE	8.21	4.9	6.48	4	3.48	2.28

Fig 4. RMSE, MSE, and MAE values of the projected HSTM-RL-PPO are compared to those of other methods.

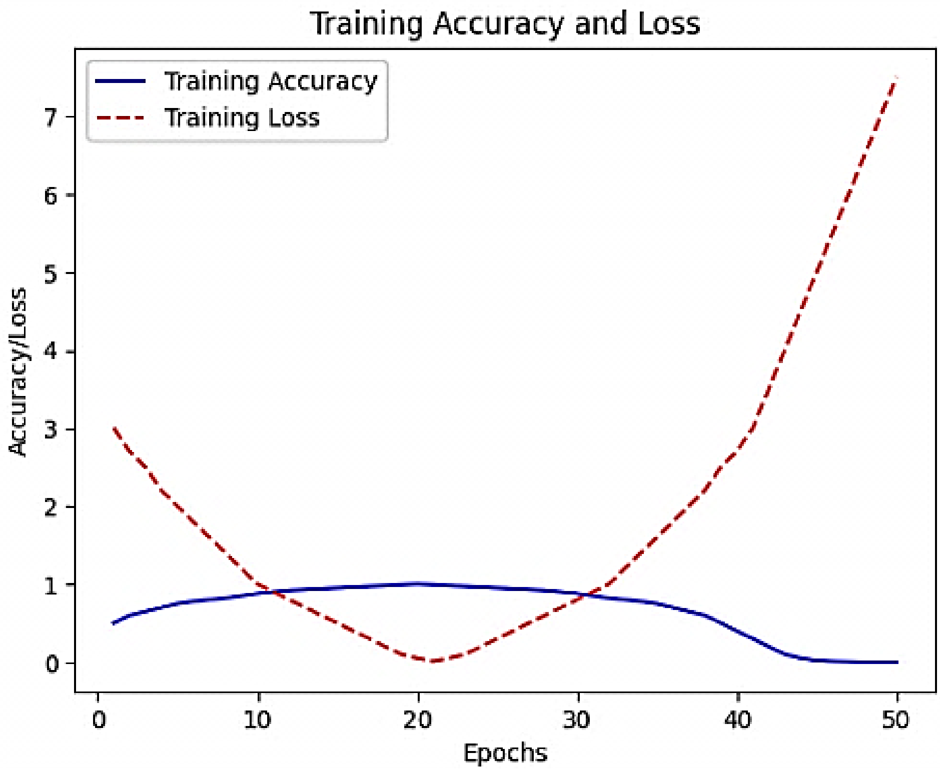


Fig 5. Training Loss vs. Accuracy of Training for the HSTM-RL-PPO

As a result, the HSTM-RL-PPO model surpasses other algorithms in terms of accuracy [37], precision [37], recall [37], and demonstrates reduced RMSE [37], MSE [37], and MAE [37], establishing itself as most efficient method for demand response prediction. The training process for the HSTM-RL-PPO model involves utilizing a sample dataset containing historic energy ingestion data, meteorological information, and other significant variables to estimate a building's energy usage. This model studies to predict energy ingestion based on input parameters and generates forecasts for building's energy usage in upcoming hour.

For occasion, the model can be fed with input data like occupancy, temperature, moistness, and past energy usage to predict the expected energy needs for the next hour. Utilizing this forecast, adjustments can be made to the demand response plan. Homeowners might be encouraged to reduce their energy consumption, such as turning off lights or adjusting the thermostat, if the prediction indicates higher energy usage than anticipated. By employing the HSTM-RL-PPO model for energy consumption prediction and augmenting demandresponse strategies, there is potential to diminish overall energy expenditure, particularly during peakdemand periods.

4.3 Outcomes for Operative Load Distribution with Suggested TRPO-RL-SA Method

Efficient load balancing is a perilous factor in optimizing performance of hybrid renewable energy systems. The effective distribution of the load among multiple energy sources is essential for maximizing overall efficiency. To achieve this, intelligent control systems show a decisive role in analyzing data associated to energy production and consumption, influencing the most efficient load balancing techniques. Employing reinforcement learning within the realm of artificial intelligence emerges as a valuable approach for improving load balancing in hybrid greenenergy systems.

The process entails development of strategies to allocate energy loads among various sources, informed by the careful analysis of electricity creation and expenditure patterns. These approaches are then gradually reinforced over time through the utilization of metaheuristic optimization algorithms. These algorithms adapt to evolving patterns in energy production and consumption, ensuring a dynamic and responsive approach to load balancing. This integration of reinforcement learning and artificial intelligence contributes significantly to enhancing overall effectiveness and performance of hybrid renewable energy systems.

Effective load balancing was evaluated using the dataset from "Open Power System Data [13]," which offers detailed statistics on the production, use, and transmission of energy throughout Europe. To tailor the dataset for this study, a number of attributes are either removed or combined to provide a more refined collection of features. The characteristics that have been selected for load balancing analysis include electricity creation, energy consumption, energy demand, energystorage capacity and efficiency, energy distribution strategies, the proportion of renewable energy compared to conventional sources, and overall system efficiency. The sampledataset employed is listed in below Table 2.

Table 2. A sample of the load balancing dataset

Time	Solar Production (kW)	Wind Production (kW)	Traditional Production (kW)	Energy Demand (kW)	Energy Storage Level (kWh)	Energy Surplus (kW)	Energy Deficit (kW)
1	20	25	30	50	100	25	0
2	25	30	30	60	90	25	0
3	30	35	35	70	80	30	0
4	25	40	40	80	70	25	0
5	20	45	40	90	60	5	5

6	15	40	35	80	50	0	0
7	10	35	30	70	40	0	0
8	5	30	25	60	30	0	0
9	0	25	20	50	20	0	0
10	0	20	15	40	10	0	0

The proposed study employs certain performance criteria to effectively monitor load balancing outcomes, even if loadbalancing itself is not a classification problem. A few of these measures are energy surplus/deficit, frequency and duration of outages, energystorage efficiency, and expenses associated with electricity creation and use. The suggested TRPO-RL-SA algorithm's load balancing results are compared to those of existing algorithms, including ArtificialNeuralNetwork, DecisionTrees, and SupportVectorMachine, based on a few criteria. Assessing load balancing algorithms involves the computation of energy surplus or deficit, comparing estimated energy production and consumption figures generated by the algorithms with the actual data. This comparison permits for the assessment of accuracy [37], precision [37], recall [37], and the F1 score [37]. Furthermore, a critical consideration involves the examination of frequency and extent of outages, leveraging dataset analysis to gain insights into the average occurrence and duration of power interruptions. Performance metrics [37] such as accuracy [37], precision [37], recall [37], and the F1 score are computed by aligning the anticipated values with the actual standards derived from the algorithms.

Energy storage efficiency serves as another vital criterion for assessing the efficacy of the load balancing process. Through thorough examination of the dataset, it becomes possible to quantify the amount of saved and utilizable energy. Accuracy, precision, recall, and the F1 score are calculated by associating the projected energy storage efficiency benchmarks from the procedures with the authentic values.

The evaluation of the cost associated with energy generation and consumption stands as a crucial component in appraising load balancing solutions. Dataset analysis facilitates the estimation of the overall cost of energy generation and consumption within the energy system. A comparative analysis, aligning the predicted total cost values generated by the algorithms with the factual values, enables the assessment of accuracy, precision, recall, and the F1 score. These metrics enable a comprehensive evaluation to pinpoint the most suitable load balancing strategy for a given energy system.

In Figure 6, the anticipated performance of the proposed TRPO-RL_SA algorithm for energy surplus estimation is depicted, highlighting its superior accuracy, precision, and recall in contrast to other algorithms such as ANN, decision trees, and SVM. The results affirm the efficacy of the TRPO-RL_SA algorithm in enhancing precision and recall for energy surplus forecasts. Figure 7 offers a comparative analysis of the TRPO-RL_SA algorithm with established algorithms like ANN, decision trees, and SVM concerning outage frequency and length. The findings unequivocally demonstrate the superior performance of the TRPO-RL_SA algorithm, showcasing higher accuracy, precision, recall, and F1 scores in outage prediction and management compared to the other algorithms under consideration.

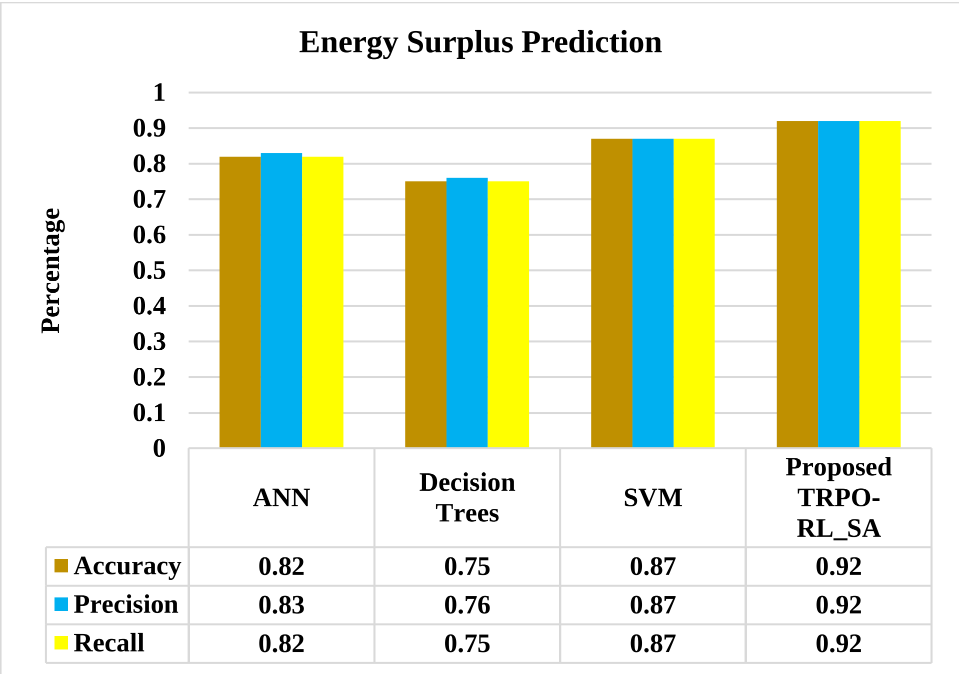


Fig 6. Prediction of energy surplus using the suggested TRPO-RL-SA algorithm

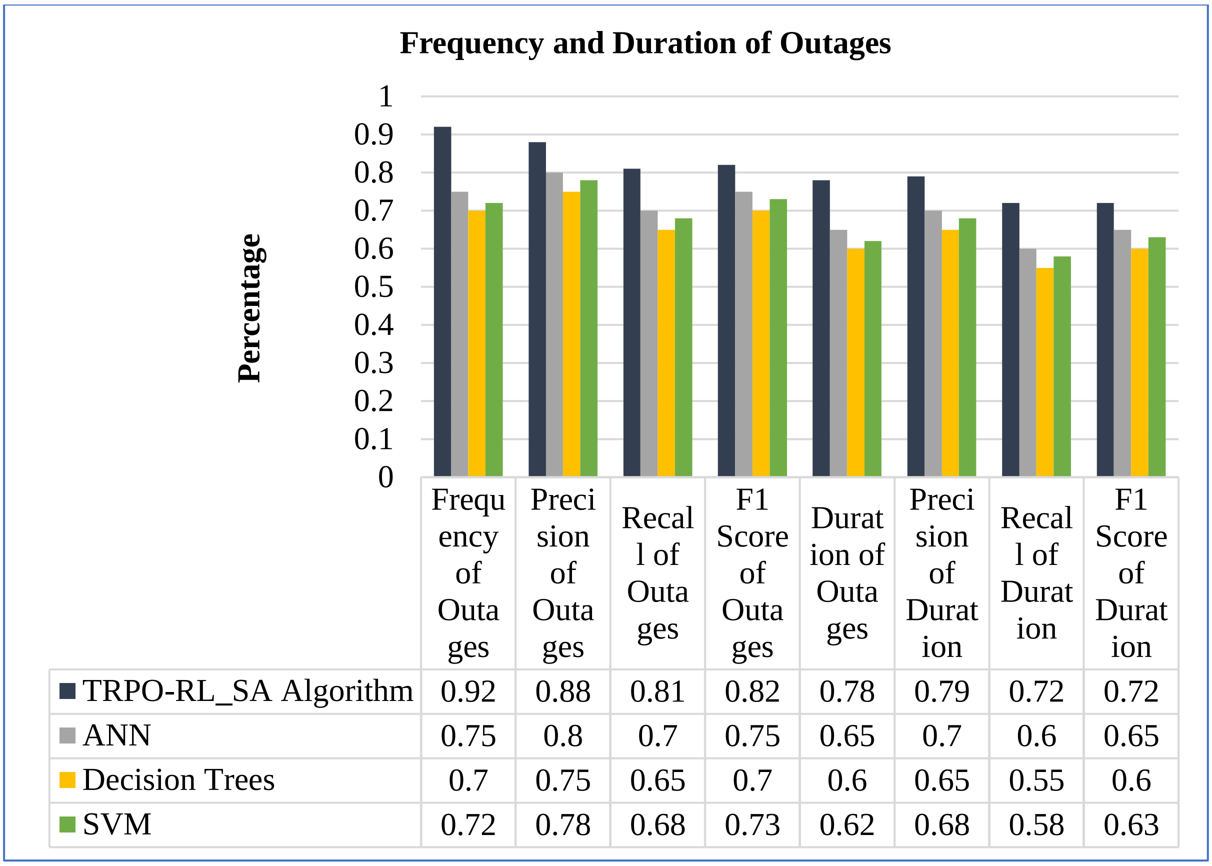


Fig 7. In comparison to the current hybrid TRPO-RL-SA, the frequency and length of outages under the proposed proposal

A thorough approach to assess the energy storage efficiency of the dataset involves analyzing the release and conservation of energy within the system over a specific timeframe. Following this, a comparison is conducted between the projected energy storage efficiency and the actual data generated by diverse load balancing strategies.

As illustrated in Figure 8, the outcomes of the comparative study encompass the current ANN, decision trees, and SVM algorithms, alongside the recommended hybrid TRPO-RL-SA technique. A detailed examination of Figure 8 underscores the superior performance of the suggested hybrid TRPO-RL-SA method. It surpasses ANN, decision trees, and SVM by significant margins of 7%, 13%, and 4%, 6%, 14%, and 3%, and 8%, 12%, and 6%, respectively, in terms of accuracy, precision, and recall. These findings emphasize the dominance of the hybrid TRPO-RL-SA algorithm over the other algorithms under scrutiny, validating its efficacy in optimizing energy storage efficiency.

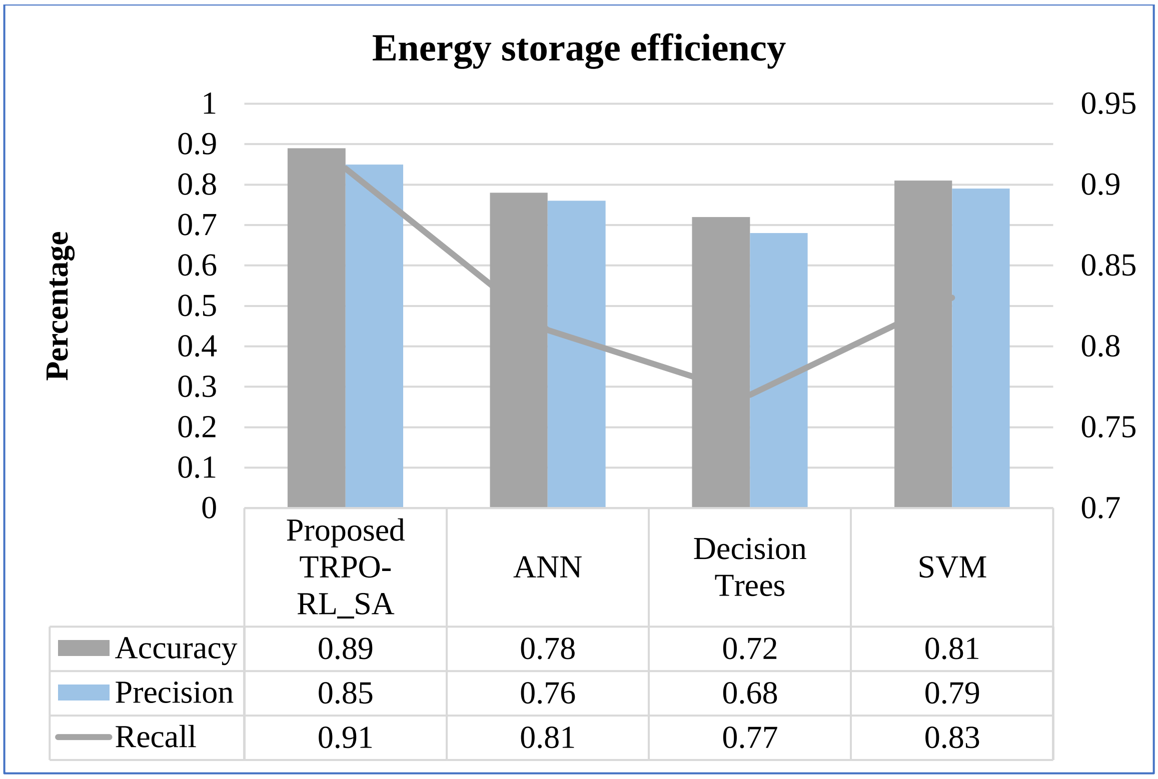
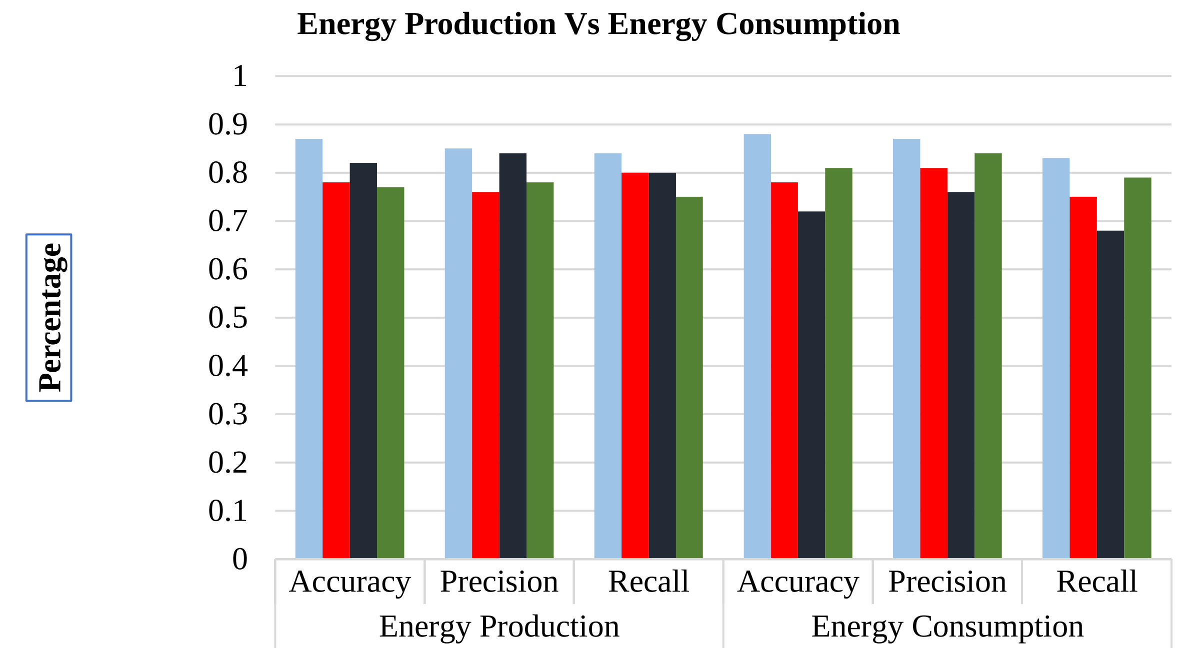


Fig 8. Power Retention The suggested TRPO-RL-SA's efficiency compared to the current

Figure 9 exhibits the data related to energy generation and consumption, employing the recommended Hybrid Trust Region Policy Optimization with Reinforcement Learning and Simulated Annealing (TRPO-RL-SA) algorithm. The implementation of the TRPO-RL-SA algorithm enhances the patterns of energy production and consumption, highlighting the superior performance of the suggested strategy in comparison to existing techniques that yielded suboptimal outcomes.

Consequently, the proposed TRPO-RL-SA algorithm stands out as an exceptionally effective tool for evaluating load balancing, surpassing previous algorithms in terms of accuracy across various load balancing criteria. These criteria encompass the algorithm's capability to predict energy surplus, anticipate the frequency and duration of outages, assess the efficiency of energy storage, and analyze energy production and consumption. The heightened accuracy metrics underscore the algorithm's success in balancing variations in energy supply and demand through proficient forecasting and management, ultimately leading to improved load balancing. The integration of reinforcement learning and simulated annealing in decision-making processes, energy storage, distribution, and consumption further contributes to the algorithm's overall effectiveness.



	Energy Production			Energy Consumption		
	Accuracy	Precision	Recall	Accuracy	Precision	Recall
TRPO-RL_SA	0.87	0.85	0.84	0.88	0.87	0.83
ANN	0.78	0.76	0.8	0.78	0.81	0.75
Decision Trees	0.82	0.84	0.8	0.72	0.76	0.68
SVM	0.77	0.78	0.75	0.81	0.84	0.79

Fig 9. Production and Consumption of Energy The suggested hybrid TRPO_RL_SA's efficiency in relation to the current

4.4 Predicting and overseeing the production of renewable energy through the proposed hybrid CNN-PSO approach.

To construct an ideal dataset for predicting renewable energy output, it is essential to compile historical data encompassing diverse factors influencing renewable energy development. These factors include solar radiation, weather patterns, energy production, consumption, and storage. Leveraging this comprehensive dataset, a machine learning model predicting renewable energy generation can be developed, incorporating a variety of inputs. The continuous improvement of the model's performance and accuracy can be achieved by employing advanced techniques such as Convolutional Neural Network (CNN) and Particle Swarm Optimization (PSO). The data for the hybrid CNN-PSO renewable energy forecasting and management model was sourced from "Open Power System Data," a public organization releasing power-related information [13].

Table 3 presents the sample dataset used for prediction, featuring key characteristics:

Timestamp: Records the time of data recording.

Solar Energy Generation (kW): Represents the energy produced through solar power.

Wind Energy Production (kW): Signifies the electricity generated by wind sources.

Conventional Energy Production (kW): Denotes energy produced from traditional resources like fossil fuels.

Hourly Energy Demand (kW): Reflects the quantity of energy expended per hour.

Energy Storage Capacity (kWh): Indicates the remaining energy in sequences or other storage devices at the conclusion of each period.

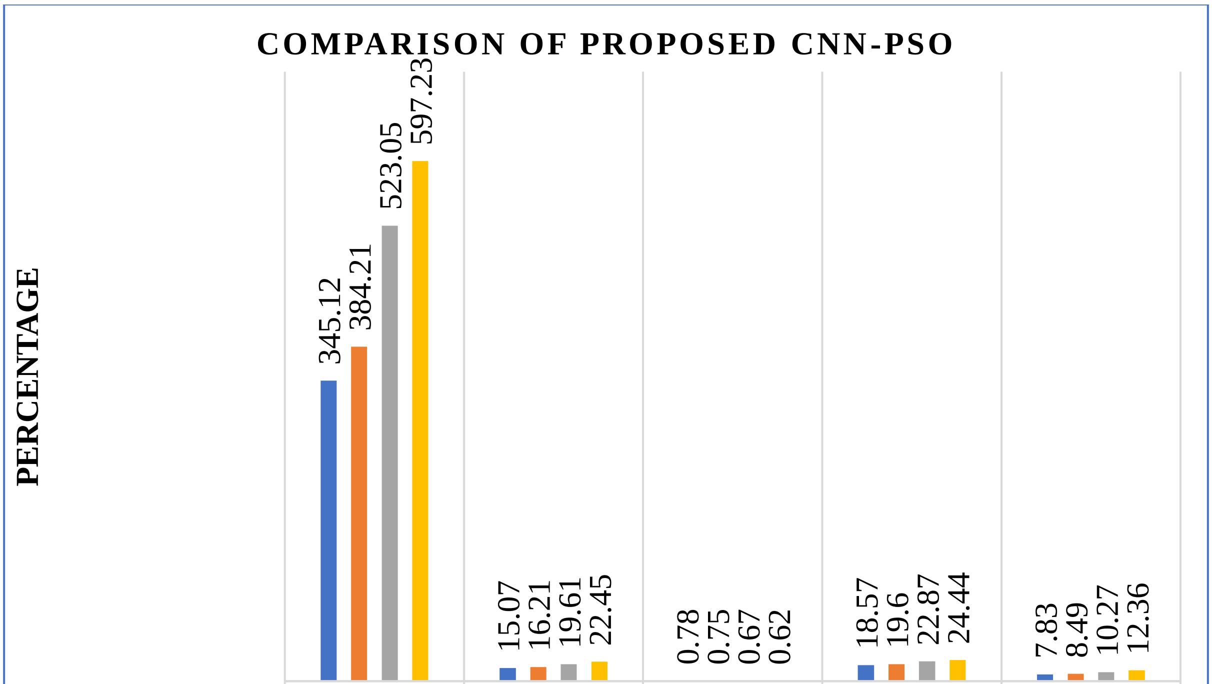
A comprehension of these variables is pivotal for understanding energy generation, consumption, and storage, serving as the groundwork for developing a renewable energy generation forecasting model. The effectiveness of the projected hybrid CNN-PSO algorithm is assessed using performance evaluation metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared (R2) score, Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) [37].

Table 3. Sample of the dataset used to predict the output of renewable energy

Time	Solar Production (kW)	Wind Production (kW)	Traditional Production (kW)	Energy Demand (kW)	Energy Storage Level (kWh)	Renewable Energy Production (kW)
2022-01-01 00:00:00	250	1000	800	1200	200	1250
2022-01-01 01:00:00	200	800	700	1100	150	1000
2022-01-01 02:00:00	150	700	600	1000	100	850
2022-01-01 03:00:00	100	600	500	900	50	700
2022-01-01 04:00:00	50	500	400	800	0	550
2022-01-01 05:00:00	0	400	300	700	0	400
2022-01-01 06:00:00	0	300	400	800	50	300
2022-01-01 07:00:00	50	400	500	900	100	450
2022-01-01 08:00:00	100	500	600	1000	150	700

2022-01-01 09:00:00	150	600	700	1100	200	850

The Mean Squared Error (MSE) delivers an estimation of the overall difference or typical squared deviation among expected and authentic standards. Mean Absolute Error (MAE) measures the normal linear distance, or normal difference, between the expected and actual values. The R2 score calculates the quantity of the reliant on variable's variance clarified by the independent variables. Root Mean Square Error (RMSE) represents the mean squared alterations between predictable and real values. Mean Absolute Percentage Error (MAPE) computes the average percentage alteration between actual and anticipated values. Lower values for each of these indicators suggest that the regression perfect is more proficient in accurately forecasting the target variable.



	MSE	MAE	R2 Score	RMSE	MAPE
CNN-PSO	345.12	15.07	0.78	18.57	7.83
CNN	384.21	16.21	0.75	19.6	8.49
SVM	523.05	19.61	0.67	22.87	10.27
Decision Trees	597.23	22.45	0.62	24.44	12.36

Fig 10. Renewable Energy Forecasting in comparison with CNN, SVM and Decision Trees

The outcomes depicted in Figure 10 reveal that the CNN-PSO algorithm outperforms competing techniques across all evaluation metrics, with the exception of MAPE, where SVM holds a slight advantage. Based on the dataset characteristics and the selected assessment criteria, it can be concluded that the CNN-PSO algorithm stands out as the most effective approach for predicting renewable energy generation.

5. CONCLUSION

The study grants a complete strategy for maximizing renewable energy output within the context of a smart grid. The HSTM-RL-PPO model emerges as a dependable approach for optimizing renewable energy generation, outperforming previous algorithms in predicting energy demand patterns, boasting accuracy, precision, and recall rates of 0.93, 0.94, and 0.92, respectively. As a robust load balancing measurement tool, the TRPO_RL_SA algorithm achieves an accuracy level of up to 0.92 across various load balancing parameters. The CNN-PSO algorithm proves to be the most successful in predicting renewable energy output, delivering maximum accuracy with metrics such as 345.12 mean squared error (MSE), 15.07 mean absolute error (MAE), 0.78 R-squared, 18.57 root mean square error (RMSE), and 7.83 mean absolute percentage error (MAPE).

In the realm of smart grids, these findings endorse the establishment of hybrid power systems driven by renewable energy sources, essential for generating and delivering affordable, dependable, and efficient electricity. Through the integration of artificial intelligence and accurate optimization techniques, this approach delivers a practical means for proactive planning and control of renewable energy production, applicable even in remote and off-grid locations. Despite the model's commendable performance, it's crucial to acknowledge limitations related to computational complexity and the reliance on trustworthy input data, particularly in large-scale systems. Future research avenues may explore expanding data sources, exploring diverse machine learning methods and optimization techniques, assessing energetic valuing models and demand response strategies, among other considerations, to address these constraints.

Considering recognized limitations, our study robustly advocates for the advancement of hybrid renewable power systems within smart grid environments. These systems are deemed crucial for delivering dependable, cost-effective, and efficient electricity generation and distribution. The suggested methodology offers a pragmatic approach to forecast and control renewable energy generation by integrating mathematical optimization methods and artificial intelligence. Because of its versatility, it may also find use in off-grid and rural areas, away from smart grids. Our finding should encourage more research in this area, enhancing the efficacy and efficiency of energy management systems.

Conflict of interest/financial disclosure

There is no conflict of interest to disclose and there is no Informed consent in studies with human subjects and Animal studies

Data Availability

No Data availed for this research article

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