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Research paper

AI-enabled metaheuristic optimization for predictive management of renewable energy production in smart grids

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A B S T R A C T

The integration of renewable energy sources into smart grids offers a promising solution for building sustainable and reliable energy systems. However, optimizing hybrid renewable energy systems remains a crucial area of research. The study presents a comprehensive approach combining artificial intelligence algorithm techniques with metaheuristic optimization algorithms for anticipating and managing renewable energy sources in smart grid environments. With precision, recall, and accuracy scores of 0.92, 0.93, and 0.92, respectively, the proposed Hybrid LSTM-RL model beats current algorithms in correctly forecasting energy demand patterns. With an accuracy of 0.91 for various load balancing measures, the RL-SA algorithm efficiently measures load balancing. With mean squared error (MSE), mean absolute error (MAE), R-squared score, root mean square error (RMSE), and mean absolute percentage error (MAPE) values of 345.12, 15.07, 0.78, 18.57, and 7.83, respectively, the CNN-PSO algorithm also turns out to be the most successful at forecasting the generation of renewable energy. These discoveries help hybrid renewable energy systems in smart grid settings advance, enabling effective, dependable, and economical energy production and distribution. The suggested solution also has the potential to be used in rural and off-grid settings. Overall, this research offers a useful method for maximizing the production of renewable energy and acts as a spark for additional studies into energy management systems.

1. Introduction

Smart grids represent a significant advancement in energy management and distribution. These intelligent electrical grids utilize progressive sensors, communication, and regulator technologies to augment the generation, supply, and consumption of electricity (Islam et al., 2022). The importance of smart grids is multi-faceted, including increased reliability by detecting and responding to issues automatically, resulting in reduced downtime for businesses and households. Additionally, smart grids enhance energy efficiency by minimizing waste and optimizing the usage of renewable energy sources, enabling better incorporation of renewable sources like solar and wind power, and handling the variability of these sources efficiently. This increased efficiency can also help to reduce the overall cost of electricity by minimizing the need for new power plants and transmission lines while reducing energy waste. Furthermore, smart grids (Mahmud et al., 2020) can enhance energy management by providing consumers with more information about their energy consumption and helping them manage it more effectively, thereby promoting a more sustainable use of energy and potentially leading to lower energy bills. Thus, smart grids offer a range of benefits, including improved reliability, efficiency, and sustainability of the electricity system, as well as cost savings and enhanced energy management for consumers.

The implementation of smart grids has become increasingly important in current years, and Internet of Things (IoT) has played a critical role in this development. IoT devices and technologies have enabled the collection and analysis of real-time data from a range of sources, which is essential for optimizing the generation, delivery, and consumption of power in a smart grid.

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The significance of the IoT in smart grids can be summarized as follows (Tightiz and Yang, 2020; Bajpai and Dash, 2012):

- Real-time monitoring: IoT devices have the capability to provide real-time monitoring of critical parameters, such as energy usage and power quality. This information is essential for detecting and responding to issues quickly, ensuring the reliability of the grid.
- Advanced analytics: IoT devices and platforms provide advanced analytics capabilities, enabling the analysis of large volumes of data from multiple sources, including smart meters and sensors. This analysis could be used to optimize the generation, delivery, and consumption of electricity in smart grids.
- Predictive maintenance: IoT devices can be utilized for predictive maintenance of the grid infrastructure, allowing utilities to identify and address issues before they cause outages or other problems.
- Demand response: IoT devices and platforms facilitate demand response programs, incentivizing consumers to decrease their energy utilization during crowning periods. This helps to diminish peak demand, optimize the utilization of renewable energy sources, and enhance the overall efficiency of the grid (Bajpai and Dash, 2012).
- Integration of distributed energy resources: IoT devices can ease integration of distributed energy resources, such as solar panels and wind turbines, into the grid. Although integration can be challenging, IoT technologies can help manage the variability of these resources and ensure their efficient use (Zhang et al., 2021).

Thus, IoT is critical for the development and implementation of smart grids, as IoT devices and technologies provide real-time monitoring, advanced analytics, predictive maintenance, demand response capabilities, and ease integration of distributed energy-resources. All of these elements are crucial for optimizing the performance and efficiency of a smart grid.

Hybrid Renewable Energy Systems (HRES) offer reliable and legitimate energy sources for smart grids by combining multiple renewable sources. Benefits include increased reliability, improved efficiency, enhanced flexibility, reduced environmental impact, and cost-effectiveness. These systems optimize energy production, reduce waste, and ensure a stable energy source for the future. In the proposed work, optimization algorithms combined with artificial intelligence techniques are utilized to optimize hybrid generable energy systems.

The remaining sections of the paper are structured as follows. Section 2 provides a comprehensive overview of recent research conducted in the proposed area. It discusses various studies and approaches that have been explored, highlighting their strengths and limitations. Section 3 outlines the methods employed in this research to achieve the desired results. It provides a detailed explanation of the Hybrid LSTM-RL model, the RL-SA algorithm, and the CNN-PSO algorithm, describing the steps taken to implement and evaluate these methodologies. In Section 4, the obtained results are compared with existing works in the field. The performance of the proposed models and algorithms is analysed in relation to previous approaches, offering insights into their effectiveness and superiority. Finally, Section 5 presents a conclusive summary of the research. It summarizes the main findings and contributions, discusses the potential implications and suggests future research directions.

2. Related work

In the realm of IoT-based smart grids, numerous techniques have emerged to bolster their capabilities, spanning across communication, power, and energy management domains. It provides a range of these techniques that cover genuinetime monitoring, data analytics, predictive maintenance, demand reaction, integrating renewable energy sources and cybersecurity (Islam et al., 2022). The paper draws attention to their benefits but also discusses the challenges and provides valuable guidelines for further research in this area. The integration of renewable energy sources is the subject of a proposal to leverage Internet of Things technology and use Big Data Analytics, in order to facilitate timely monitoring and control of electricity usage, make it possible to integrate renewables into demand response schemes as well as implementation of Demand Response Programmes (Mahmud et al., 2020). The integration challenges are clearly identified, accompanied by future research directions aimed at tackling them effectively.

In their endeavour to implement hybrid renewable energy systems, Said et al. (2018) advocates for the combination of a number of renewables with storage facilities in order to tackle intermittentity and optimize grid integration performance. The paper offers a thorough discussion of the benefits and challenges posed by these systems, providing an insight into potential avenues to continue research and innovation. The review focuses on the achievements of the Internet of Things driven smart grid systems, including the use of various recommended techniques, such as real time monitoring and control of energy consumption, seamless integration of renewable energy sources into the grid, the implementation of the Demand Response Programme, optimization of the use of big data and machine learning, and the protection of robust cybersecurity (Tightiz and Yang, 2020). The report highlights prospects of future research and development in this area, supported by a comprehensive evaluation of the benefits and challenges facing smart grid systems that rely on Internet of Things technology.

In addition, it sets out a comprehensive overview of the utilization of internet of things technologies in smart grids with particular emphasis on overcoming challenges related to implementation (Bajpai and Dash, 2012). In order to address the problem of intermittency, this document covers techniques for hybrid energy systems incorporating different types of renewables such as solar panels, wind turbines, water and biomass combined with energy storage schemes. Consideration is given to advanced control and monitoring techniques as well as seamless grid integration. The paper is intended to initiate a roadmap for the development of R&D opportunities in this dynamic area.

In the context of 5G vertical industries, Zhang et al. (2021) introduces several techniques for implementing energy management agent frameworks (EMAFs). Such methods make it possible to communicate and coordinate between different devices and systems through the use of Multi Agent Systems, which creates Scalable and Flexible Architectures that are easily adapted for a wide variety of applications and scenarios. The paper highlights the importance of incorporating EMAFs into 5G networks in order to monitor and control energy consumption at real time. The study provides an overview of the potential benefits and challenges related to EMAFs, identifies areas for further research and development in this area. Proposed in Eltamaly et al. (2021), a novel demand-response scheme for sizing hybrid energy systems (HESs) incorporates demand response programs with HES to enhance the energization of end-users and optimize grid performance. The study recommends that advanced control algorithms such as prediction models are used for obtaining a stable and reliable energy source. In addition, in view of the uncertainty related to renewable energy sources and electricity demand, an optimization model is being developed for determining the optimum size of the Hydrogen Energy Storage System. The potential advantages and disadvantages of the proposed technique are thoroughly analysed in this paper, highlighting opportunities for further R&D.

Tazay et al., 2020 developed an autonomous hybrid renewable energy system (HRES) specifically designed for a university in Saudi Arabia. The primary objective is to establish a reliable and consistent energy supply by combining solar and wind power sources with battery storage. The viability and economic feasibility of this HRES concept are evaluated through a comprehensive technical analysis. This analysis considers crucial factors such as initial investment, operational expenses, energy conservation, and the time it takes to recover the investment. To enhance the operational efficiency of the HRES and facilitate its smooth integration with the university's electrical grid, advanced monitoring and control methods are employed. The paper addresses various challenges associated with implementing the HRES, including the intermittent nature of renewable energy sources, the limitations of batteries, and the necessity for effective system maintenance and management. By emphasizing the potential of the proposed HRES, the study aims to significantly reduce the university's carbon footprint, enhance overall energy efficiency, and yield substantial economic advantages.

To enhance power distribution and source resizing in a highly available island microgrid for a petroleum platform in Tunisia, Abidi et al. (2019) recommends integrating renewable energy sources, such as solar and wind power, to decrease reliance on fossil fuels and promote microgrid sustainability. The report suggests a more efficient approach for the distribution of energy, which would use a hierarchical control system in order to provide stability and reliability at various load levels. In addition, an optimization model is suggested that will enable micro grids to be more efficient and cost effective by identifying the optimum size of energy sources and energy storage systems.

Conducting a pervasive economic and sensitivity analysis of a hybrid renewable energy system (HRES) is the focus of Sawle et al. (2021). The study proposes to perform an economic viability and sensitivity assessment of the HRES in relation to different input parameters and uncertainties using a Monte Carlo simulation approach. In view of the cost of capital and operational costs, energy efficiency savings as well as payback periods, a techno economic analysis framework is proposed. Furthermore, the sensitivity analysis methodology is used to identify which input parameters and uncertainties have an impact on HRES's business performance. In order to determine optimum weighting and configuration of HRES components, this paper emphasizes the inclusion of an optimization model with a view to maximizing monetary benefits. In addition, the study examines the integration of energy storage and demand response mechanisms into the HRES analysis.

2.1. Research gap analysis

After reviewing the literature, several research gaps have emerged in the field of IoT-based smart grid systems (Swastika et al., 2017) and hybrid renewable energy systems (Krishna and Kumar, 2015). The paper presents a novel approach by integrating and exploiting three main techniques, such as power response, load balancing and forecasting of energy usage in the Smart Electricity System environment, to optimize Hybrid Renewable Energy Systems. The novelty is the demonstration of the synergistic effects of combining these techniques, which have traditionally been studied in isolation in previous works. The aim of this study is to exploit the full potential of Internet of Things, Smart Grid technologies and Hybrid Renewable Energy Systems by solving these research gaps. Optimization of Hybrid Renewable Energy Systems is an essential aspect of the proposed work (Palej et al., 2019). In the smart grid context, such optimization is of vital importance in ensuring efficient, reliable and cost effective energy generation and distribution. A combination of strategies including demand response, energy storage, load balancing and accurate Renewable Energy Forecasts are being employed to this end, supported by sophisticated Analytics and Data Management Tools as described below (Kovács, 2018; Wang et al., 2017, 2019). The objective is to ensure energy production and distribution in the most efficient and sustainable way, which would result in reliable and secure energy supplies by means of implementation of these strategies (Khan et al., 2022). The model proposes to exploit AI techniques in conjunction with optimization algorithms for the effective management of demand response, load balancing and renewable energy forecasting strategies (Hasan et al., 2019; Ahmad et al., 2022; Zhang et al., 2022).

Thus, optimizing hybrid renewable-energy systems in a smart grid environment requires a combination of these techniques, along with advanced analytics and data management tools. Employing these strategies ensures that energy is generated and distributed in the most efficient and cost-effective manner possible, ensuring a reliable and sustainable energy supply. Thus in the proposed model, artificial intelligence techniques together with optimization algorithms are utilized to manage demand response, load balancing and renewable energy forecasting strategies.

3. Materials and methods

Artificial intelligence (AI) techniques, when combined with optimization algorithms, can play a critical role in managing demand response, load balancing, and renewable energy forecasting in hybrid renewable energy systems operating in a smart grid environment (Khan et al., 2022).

- *Demand Response*: To predict energy demand patterns and identify opportunities for demand response, a novel long short-term memory and reinforcement learning (LSTM-RL) is proposed. By analysing data on energy consumption patterns, weather conditions, and other variables, these techniques can determine when demand is likely to be high and when it can be reduced. Optimization algorithms can then be used to create strategies for managing demand response, such as prioritizing it based on the cost of energy at distinct times, or on the availableness of renewable energy (Hasan et al., 2019).
- *Load Balancing*: Reinforcement learning is an AI technique that can optimize load balancing in a hybrid renewable energy system (Ahmad et al., 2022). By analysing energy production and consumption patterns, strategies for balancing energy loads across different sources are developed. Metaheuristic optimization algorithms are then employed to refine these strategies over time, based on changes in energy production and consumption patterns.
- *Renewable Energy Forecasting*: AI techniques such as neural networks and decision trees can be utilized to forecast renewable energy production (Zhang et al., 2022). By utilizing data on weather patterns, historical energy production, and other variables, these techniques can predict how much energy will be produced by renewable sources. Metaheuristic optimization algorithms are then used to develop strategies for managing renewable energy production based on these forecasts. One potential application of energy storage systems is to store surplus renewable energy generated during periods of high production and utilize it when production levels are low. This enables the efficient utilization of renewable energy resources by balancing the supply and demand dynamics.

The combination of AI techniques and metaheuristic optimization algorithms can significantly improve the efficiency and reliability of hybrid renewable-energy systems in a smart grid environment. To predict and manage renewable energy production, a

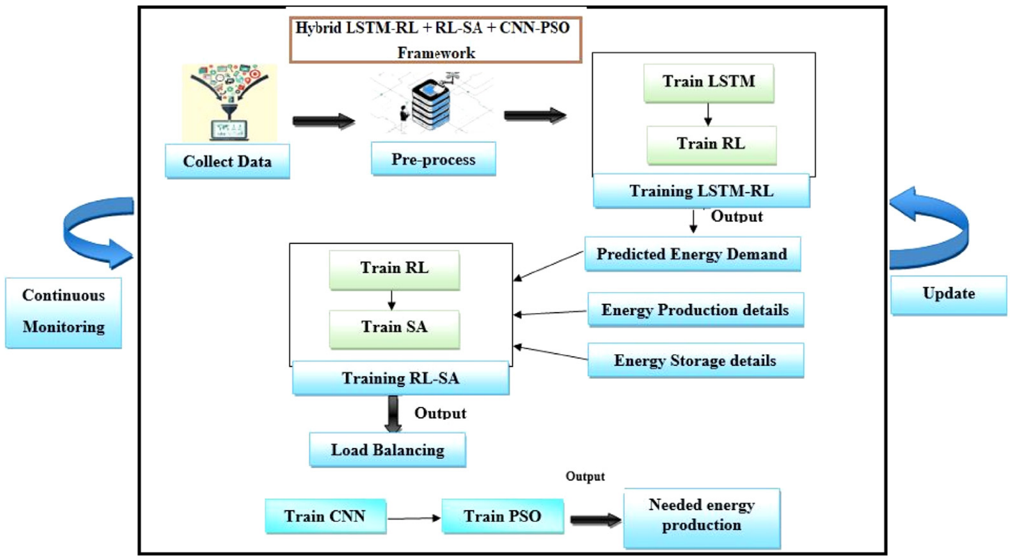


Fig. 1. Hybrid LSTM-RL+RL-SA+CNN-PSO framework for smart grids.

hybrid approach combining LSTM-RL, RL-SA, and CNN-PSO techniques is utilized. The solution comprises of three main steps: data collection and preprocessing, training and optimization, and implementation, and monitoring.

- *Step 1*: In the first step, data on historical energy consumption, weather patterns, and other relevant variables are collected and pre-processed for use in the models.
- *Step 2*: In the second step, the LSTM-RL technique is used to predict energy demand patterns, while RL-SA is employed to develop optimal load balancing strategies. Finally, CNN-PSO (Passricha and Aggarwal, 2019) is used to forecast renewable energy production and develop strategies for managing it.
- *Step 3*: The third step involves implementing the optimized strategies in the energy system and continuously monitoring system performance to ensure optimal efficiency.

By combining these three techniques, the proposed solution offers an effective and comprehensive approach to predicting and managing renewable energy production. A thorough overview of the proposed framework is illustrated in Fig. 1.

3.1. Predicting demand response using the proposed LSTM-RL

The Long Short-Term Memory (LSTM) neural network (Sak et al., 2014) is powerful tool for analysing sequential data, such as time series data in energy consumption patterns. By using LSTM, historical patterns of energy consumption can be identified and used to make accurate predictions about future energy demand. However, LSTM alone does not provide the optimal demand response strategies required to maximize efficiency and reduce costs. This is where reinforcement learning (RL) algorithms (Oh et al., 2020) come in. RL algorithms use trial-and-error methods to learn how to make optimal decisions based on rewards or penalties. By combining LSTM and RL, the system can take advantage of both techniques, using LSTM to predict energy demand patterns and RL to optimize demand response strategies based on those predictions. The hybrid LSTM-RL neural network is trained on a dataset of historical energy consumption patterns, weather conditions, and other relevant variables. The LSTM component of the network is responsible for learning and predicting patterns in energy consumption over time, while the RL component is responsible for making decisions about demand response based on those predictions.

For instance, the network can be used to predict when demand is likely to be high and when it can be reduced, based on data inputs such as weather forecasts and energy consumption patterns. These predictions can then be used to inform demand response strategies, such as adjusting the temperature in buildings, shifting energy use to off-peak hours, or utilizing energy storage systems. The RL component can use these predictions to learn which strategies are most effective and adjust them over time based on feedback. Overall, the combination of LSTM and RL techniques provides a powerful tool for optimizing demand response in hybrid renewable energy systems. By taking advantage of both techniques, the system can accurately predict energy demand patterns and make optimal decisions to maximize efficiency and reduce costs.

Algorithm: Hybrid LSTM-RL

1. Step 1: Collect data

   Historical energy consumption data, weather data, and other relevant variables were collected.
2. Step 2: Pre-process data

   Pre-process the data to prepare it for use with the LSTM-RL model.
3. Step 3: Train the LSTM model

   Train an LSTM model on the pre-processed data to predict energy demand patterns.
4. Step 4: Train the RL model

   Train the RL model to optimize demand response strategies based on the LSTM predictions.
5. Step 5: Combine LSTM and RL models

   The trained LSTM and RL models are combined into a hybrid model.
6. Step 6: Deploy the model

   Deploy the hybrid model in a real-world smart grid environment to predict energy demand patterns and optimize demand response strategies in real-time.
7. Step 7: Monitor and update the model

   Monitor the performances of hybrid model in real time and update the model as necessary to assure optimal performance.

3.2. Working of LSTM and RL in optimizing demand response

LSTM is a specialized recurrent neural network utilized to analyse sequential data, such as historical energy consumption data, to forecast future demand patterns in demand response. The input layer receives the data in a sequence, which is then processed by the LSTM layer. This layer encompasses a memory cell, input gate, output gate, and forget gate to identify patterns, determine relevant input data for storage, prevent overload with irrelevant data, and use stored information for making predictions. The output layer generates the predicted energy demand based on the LSTM layer's output. The equations for different layers are represented in Eq. (1) to Eq. (6).

$$\text{For input gate, } i_t = \sigma Y_i * [k_{t-1}, x_t] + a_i \tag{1}$$

$$\text{Forget-gate is given by, } f_t = \sigma Y_f * [k_{t-1}, x_t] + a_f \tag{2}$$

$$\text{Output\_gate is given by, } o_t = \sigma Y_o * [k_{t-1}, x_t] + a_o \tag{3}$$

$$\text{Candidate's memory cell is given by, } \check{C}_t = \tanh Y_c \dot{*} \left[k_{t-1,} x_t\right] + a_c \tag{4}$$

$$\text{Memory cell is represented by, } C_t = f_t * C_{t-1} + i_t * \check{C}_t \tag{5}$$

$$\text{Hidden state is given by, } h_t = o_t * \tanh(C_t) \tag{6}$$

Wherein i_t represents the input gate at time step t, Y_i denotes the weight matrix associated with the inputs to the input gate, $[k_{(t-1)}, x_t]$ represents the concatenated vector of the previous hidden state ($k_{(t-1)}$) and the current input (x_t). a_i represents the bias term associated with the input gate. f_t represents the forget gate at time step t, Y_f denotes the weight matrix associated with the inputs to the forget gate. a_f represents the bias term associated with the forget gate. o_t represents the output gate at time step t. Y_o denotes the weight matrix associated with the inputs to the output gate, a_o represents the bias term associated with the output gate. $\check{C}_t$ represents the candidate's memory cell at time step t., Y_c denotes the weight matrix associated with the inputs to the candidate's memory cell. a_c represents the bias term associated with the candidate's memory cell, C_t represents the memory cell at time step t. f_t represents the forget gate at time step t. C_{t-1} denotes the memory cell from the previous time step. i_t represents the input gate at time step t. h_t represents the hidden state at time step t, $\tanh(C_t)$ represents the hyperbolic tangent activation function applied to the memory cell C_t.

The accuracy of LSTM network predictions can be enhanced by adjusting its parameters through training, thereby facilitating the optimization of demand response tactics like energy consumption adjustments in response to changes in demand.

RL can optimize demand response strategies based on LSTM neural network predictions. The algorithm learns by maximizing a reward function, which incentivizes efficient and effective demand response. First, the environment is initialized with the system's current state, including the predicted energy demand and energy storage status. The action space is defined, including potential actions such as temperature adjustment or energy storage use. A reward function is then created to incentivize optimal behaviour, rewarding reduced consumption during high demand and renewable energy use while penalizing excessive consumption and non-renewable sources. The RL algorithm is run, updating over time with new data inputs, and the optimal demand response strategy is implemented. Through this approach, effective and efficient demand response strategies can be developed, reducing reliance on non-renewable energy sources.

3.3. Effective load balancing using proposed RL-SA

Effective load balancing in a hybrid renewable energy system can be achieved through the following steps by utilizing the proposed RL-SA technique:

1. First, gather data on the energy production and consumption patterns (Soyhan, 2009) of each source in the system, such as solar, wind, and traditional sources.
2. Next, reinforcement learning (RL) techniques are used to develop initial load balancing strategies that consider predicted energy demand, current energy production, and energy storage systems.
3. Then, a metaheuristic optimization algorithm, such as simulated annealing (SA) (Rere et al., 2015) is employed, to refine the load balancing strategies developed through reinforcement learning. This will enable the identification of optimal load balancing strategies that increase the use of renewable energy sources and decrease the need for outmoded energy sources.
4. Continuously monitor the load balancing system's performance and collect new data inputs. Use these inputs to update the reinforcement learning agent and refine the load balancing strategies as necessary.
5. Finally, optimized load balancing strategies, should be implemented and energy production and consumption should be adjusted to ensure the efficient and effective use of all available energy sources.

These steps are followed in the proposed model for efficient load balancing in a hybrid renewable energy system, while reducing dependence on traditional energy sources and maximizing the utility of renewable energy sources in a smart grid environment. The proposed algorithm is represented below:

Algorithm: Hybrid RL-SA

```
def effective_load_balancing(data):
    # Step 1: Initialize the reinforcement learning agent
    agent = ReinforcementLearningAgent(data)
    # Step 2: Train the reinforcement learning agent
    agent.train()
    # Step 3: Initialize the simulated annealing algorithm
    annealer = SimulatedAnnealingAlgorithm()
    # Step 4: Optimize the load balancing strategies
    optimized_strategies = annealer.optimize(agent.get_strategies())
    # Step 5: Implement the optimized load balancing strategies
    for strategy in optimized_strategies:
        strategy.implement()
    return optimized_strategies
```

In order to train it on the data available, the algorithm initially creates a reinforcement training agent. The agent's learned to take action that maximizes the reward, in this case using more renewable energy. After that, the algorithm comes up with a simulation annealing algorithm and uses an agent to optimize load balancing strategies. The simulated annealing algorithm tries to find the most efficient solution for this problem, namely a set of load balancing strategies that will increase renewable energy use. Finally, by adjusting the output of renewable energy sources and

```
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 View.

the energy consumption of the load, the algorithm implements optimized load balancing strategies.

3.4. Forecasting renewable energy production using the proposed CNN-PSO

To forecast and manage renewable energy production using the proposed CNN-PSO technique, the following steps can be taken:

1. Gather data on variables such as weather patterns and historical energy production that impact renewable energy production.
2. Develop models to predict renewable energy production based on these variables using a convolutional neural network (CNN).
3. Metaheuristic optimization algorithms such as particle swarm optimization (Thangaraj et al., 2011) are utilized to create strategies for managing renewable energy production based on forecasts.
4. Install energy storage systems, such as batteries or pumped hydro storage, to stock surplus renewable-energy during periods of higher production and issue it while production is low.
5. Continuously monitor system performance and collect new data inputs, updating the models and management strategies over time.
6. Implement the optimized strategies for managing renewable energy production in the energy system.

By implementing these measures, renewable energy production can be effectively managed, ensuring a consistent and stable energy supply while reducing dependence on non-renewable energy sources.

4. Results and discussion

4.1. Dataset

One of the data utilized in this study was obtained from the "Smart Meter Power Consumption Data in London Households (Dada et al., 2022)" dataset, which was collected and amassed by UK Power Networks and made available by London Data store News. To further enrich the dataset, we also incorporated data from the Darksky API and Acorn data from Consolidated Analysis Center, Incorporated (CACI) by utilizing a refactored version of the original dataset available on Kaggle. The categorical data were then removed from the Darksky API, resulting in the dataset exhibited in Fig. 2.

To better understand power consumption patterns, some data points were removed because they were found to have no noteworthy correlation with points in usage. These data points included weather summary, precipType, and icon. Instead, new parameters were created by categorizing available features: datetime, apparent temperature, wind force, direction of wind, and humidity. These categorical data were not used for predictive mining, but they did provide valuable insights for pre-emptive analysis of the data used in the LSTM. The important parameters to be considered in the dataset for predicting the demand response are energy consumption, details of the weather, time details, seasonality (i.e. seasonal factors like temperature), and sources of energy. The available features are utilized and other features are dropped from the dataset.

4.2. Predicting demand response

Demand response is a process of predicting and managing energy demand during times of peak usage. To achieve this, a novel model named hybrid LSTM-RL is developed, that uses various parameters such as historical energy consumption data, weather data, building characteristics, and occupancy data. These parameters are important inputs to the model, which can accurately predict future energy demand and optimize demand response strategies in real-time. For example, the model can help adjust energy usage during peak demand periods or incentivize consumers to diminish their consummation during times of higher demand. By incorporating these parameters into the model, it is possible to develop more effective demand response strategies and reduce overall energy consumption during times of peak demand. Therefore, it is essential to collect and analyse relevant data from various sources to improve the accuracy of demand response predictions and to ensure the optimal performance of the model. Apart from "Smart Meter Power Consumption Data in London Households", some other datasets that are included in the study are 'the Hourly energy demand generation and weather" dataset from Kaggle (Shi et al., 2021) and "Smart Building System" dataset from Kaggle (Dada et al., 2022). All three datasets are thoroughly studied and a sample dataset for the study is hypothetically framed considering the parameters historical energy consumption data, weather data, building characteristics, occupancy data, weather data, time details, seasonality and sources

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

Table 2
Comparing Advantages and Disadvantages of the proposed LSTM_RL model with existing algorithms.

Algorithm	Advantages	Disadvantages	Similar Outputs
Linear Regression	Simple and easy to interpret	Assumes linear relationship between variables	Predicted demand response values
Decision Trees	Non-linear relationships between variables can be captured	Can overfit easily	Predicted demand response values, feature importance
Random Forests	Non-linear relationships between variables can be captured and overfitting can be reduced	Can be computationally expensive	Predicted demand response values, feature importance
SVM	Can handle large datasets and capture non-linear relationships between variables	Can overfit easily	Predicted demand response values, feature importance
Neural Networks	Can capture complex and non-linear relationships between variables	Can be computationally expensive and require significant data pre-processing	Predicted demand response values
Hybrid LSTM-RL	Can handle sequential data and optimize demand response strategies in real-time	Requires significant data pre-processing and computational resources	Predicted demand response values, optimized demand response strategies

of energy for predicting the demand response. A sample of 500 records is framed for the study. A short insight into the data merged from all the datasets is exemplified in Table 1.

The hybrid LSTM__RL algorithm is proposed to predict the demand response. The proposed hybrid LSTM_RL is allied with other machine learning and deep learning algorithms such as Linear Regression, Decision Trees, Random Forests, Support Vector Machine (SVM) and Neural Networks technique. The advantages of the proposed model compared with other existing approaches are represented in Table 2.

The accuracy, precision and recall values obtained for the proposed hybrid LSTM_RL model are represented in Fig. 3. From Fig. 3, it is understood that the suggested model is 27%, 14%, 21%, 9% and 5% far better in accuracy outcomes than the Linear Regression (Zou et al., 2003), Random Forest (Breiman, 2001), SVM (Wang and Hu, 2005), Neural Networks (Bishop, 1994) and LSTM methods respectively. In terms of precision, the suggested model outperforms the existing algorithms Linear Regression, Random Forest, SVM, Neural Networks and LSTM by 22%, 13%, 19%, 9%, and 5% respectively. Furthermore, the recall values for the proposed are better than 24%, 15%, 22%, 9% and 5% from the linear regression, random forest, SVM, neural networks and LSTM methods respectively.

The comparison of the proposed hybrid LSTM_RL in predicting the demand response is detailed in Fig. 4. To evaluate the performance of a model, RMSE (Root Mean Squared Error) (Bishop, 1994), MSE (Mean Squared Error) (Bishop, 1994), and MAE (Mean Absolute Error) (Bishop, 1994) values are commonly used. These metrics help to quantify the errors between predicted and actual values and provide a measure of the accuracy of the model's predictions. A lower value of these metrics specifies that the model's predictions are nearer to the real values, and the errors between the predicted and actual values are smaller. However, the ideal range of values for these metrics may differ based on the specific problem and its field. Therefore, it is crucial to consider the problem context and the application necessities while determining acceptable values for these evaluation metrics. Fig. 4 details that the RMSE value for the proposed is 3.12, the MSE value is 9.73 and the MAE value is 2.25, which are as low as possible compared to the other exiting algorithms. After analysing the data, it was determined that the hybrid LSTM-RL algorithm achieved better results than other machine learning algorithms in terms of accuracy, precision, recall, RMSE, MSE, and MAE. This implies that the hybrid LSTM-RL algorithm is the most suitable method for predicting demand response and optimizing demand response strategies. The high accuracy and precision of this model could significantly decrease energy consumption during peak demand periods, resulting in cost savings and improved energy efficiency. The model is executed for 10 epochs and the salient drift in the accuracy of the model and a slip in the loss of the model during training are portrayed in Fig. 5.

Overall, from the outcomes it is clearly defined that the LSTM-RL model is the most effective algorithm in predicting demand response, as it has the highest accuracy, precision, recall, and the lowest RMSE, MSE, and MAE compared to other algorithms. Suppose we want to predict a building's energy consumption using historical energy consumption data, weather data, and other relevant variables. In that case, we can use our sample dataset to train an LSTM-RL model that learns to predict energy consumption based on the input variables. The model takes in the input variables and generates a prediction for the building's energy consumption for the next hour. For instance, we can feed the model with input variables such as historical energy consumption, temperature, humidity, occupancy, and time of day and the model generates a prediction for the next hour's energy consumption.

Based on the prediction, we can adjust our demand response strategy. For example, if the prediction shows that the building will consume more energy than expected, we can incentivize

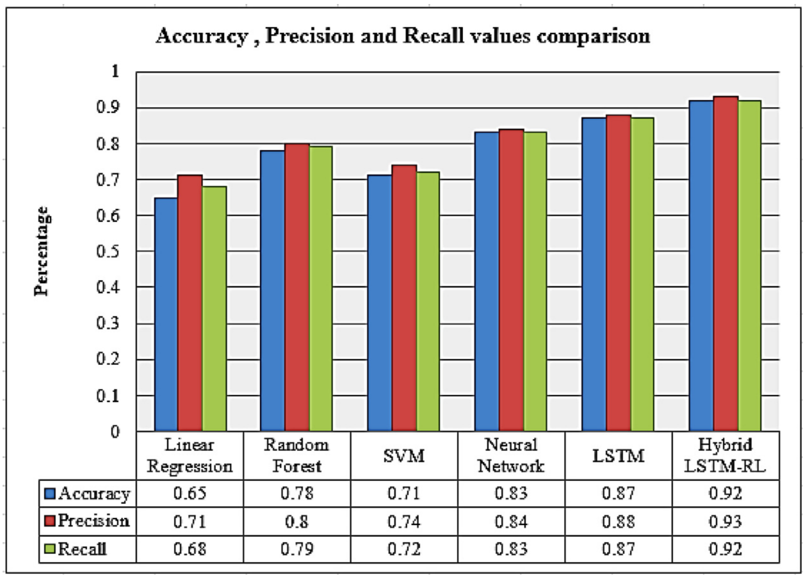


Fig. 3. Comparison of Precision, Recall and Accuracy values of the proposed hybrid LSTM-RL with existing techniques.

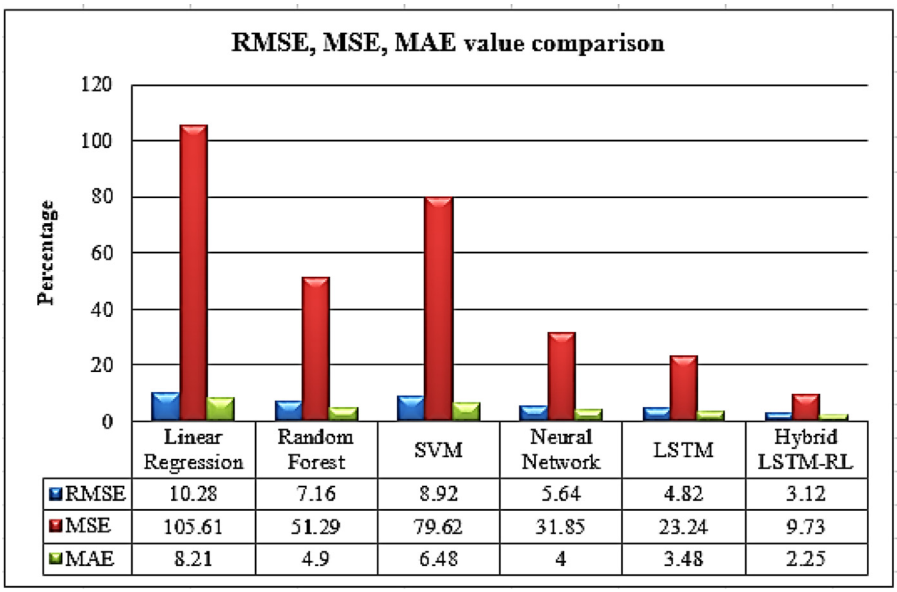


Fig. 4. Comparison of RMSE, MSE and MAE values of the proposed hybrid LSTM-RL with existing techniques.

occupants to reduce energy consumption by adjusting the temperature or turning off lights. By using the LSTM-RL model to predict energy consumption, we can optimize our demand response strategy and reduce overall energy consumption during peak demand times.

4.3. Results for effective load balancing using the proposed RL-SA technique

Load balancing is another important technique for optimizing hybrid renewable energy systems, whereby the load is distributed across different energy sources to improve overall efficiency. Intelligent control systems can be utilized to analyse data on energy consumption and production, determining the most efficient way to balance the load. Reinforcement learning is an AI technique that can optimize load balancing in a hybrid renewable energy system. By analysing energy production and consumption patterns, strategies for balancing energy loads across different sources are developed. Metaheuristic optimization algorithms are then employed to refine these strategies over time, based on changes in energy production and consumption patterns. The dataset for effective load balancing is collected from "Open Power System Data (Wiese et al., 2019)" which contains data about electricity consumption, production and transmission related data for Europe. This dataset is further refined by dropping and combining many features. Finally, the features considered for measuring load balancing are energy production, which refers to the total amount of energy generated by different sources, including solar, wind, and traditional sources. Energy Consumption, refers to the total energy used by the system or end-users. Energy demand is the amount of energy required to meet the system or end-users' energy needs. Energy storage refers to the capacity and efficiency of energy storage systems, including batteries and other storage technologies. Energy distribution is the way energy is distributed

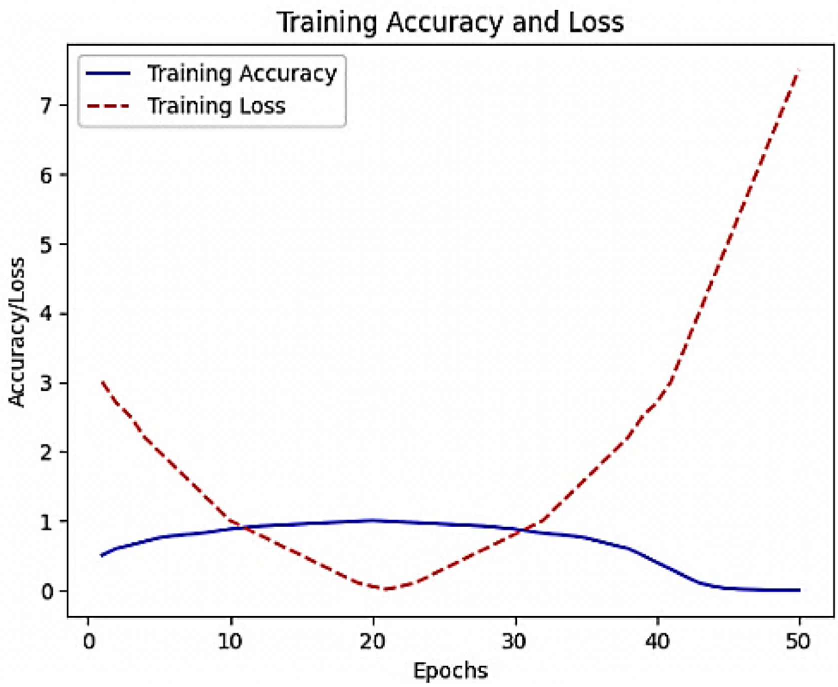


Fig. 5. Training Accuracy vs. Training Loss of the proposed hybrid LSTM-RL.

Table 3
Sample of the dataset utilized for measuring load balancing.

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

across the system, including transformers and transmission lines. Renewable energy usage indicates the proportion of energy generated from renewable-sources such as solar and wind, relative to traditional energy sources. Finally, system efficiency is the overall efficiency of the system, which takes into account energy production, storage, and distribution. The sample dataset utilized is represented in Table 3.

Since load balancing is not a classification problem, the performance metrics utilized in the proposed study to effectively monitor load balancing are energy surplus/deficit, frequency and duration of outages, energy storage efficiency and cost of energy production and consumption. To compare the outcomes of load balancing measures of the proposed RL-SA algorithm, Artificial Neural Network, Decision Trees and Support Vector Machine Algorithms are used. There are various metrics that can be used to quantify the performance of load balancing algorithms for an energy system. One such metric is the energy surplus or deficit, which can be calculated by comparing the energy produced and consumed by the system using the available dataset. The predicted energy surplus/deficit values by the algorithms can then be compared to the actual values to determine the accuracy, precision, recall, and F1 score. Another metric to consider is the frequency and duration of outages. To measure this, the dataset can be analysed to identify the number of power outages that occurred and their average duration. The predicted number and duration of outages by the algorithms can then be compared to the actual values to calculate their accuracy, precision, recall, and F1 score. Energy storage efficiency is another metric that can be used to evaluate the performance of load balancing algorithms. This can be measured by analysing the dataset to determine the amount of energy that can be stored and later released for use. The energy storage efficiency values predicted by the algorithms can then be compared to the actual values to calculate their accuracy, precision, recall, and F1 score. Finally, the cost of energy production and consumption can also be utilized as a metric to evaluate performance of load balancing procedures. The dataset can be analysed to determine the total cost of energy production and consumption in the energy system. The predicted total cost by the algorithms can then be compared to the actual values to calculate their accuracy, precision, recall, and F1 score. By comparing, the performance of load balancing procedures using the above metrics, we can determine which algorithm is the most suitable for a particular energy system.

The energy surplus prediction using the proposed RL_SA in terms of accuracy, precision and recall is represented in Fig. 6, wherein the proposed RL_SA algorithm outperforms ANN, decision trees, and SVM in terms of accuracy, precision, and recall for

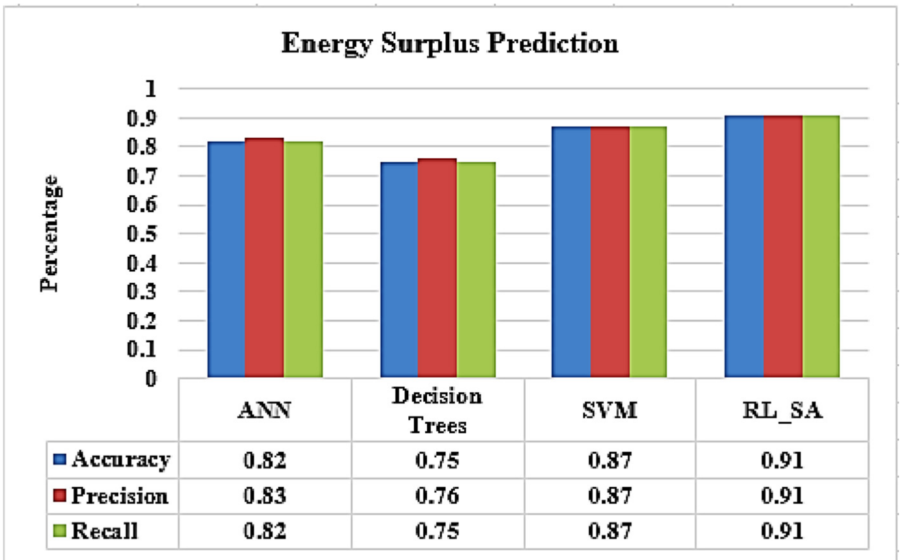


Fig. 6. Energy surplus prediction of the proposed hybrid RL-SA algorithm.

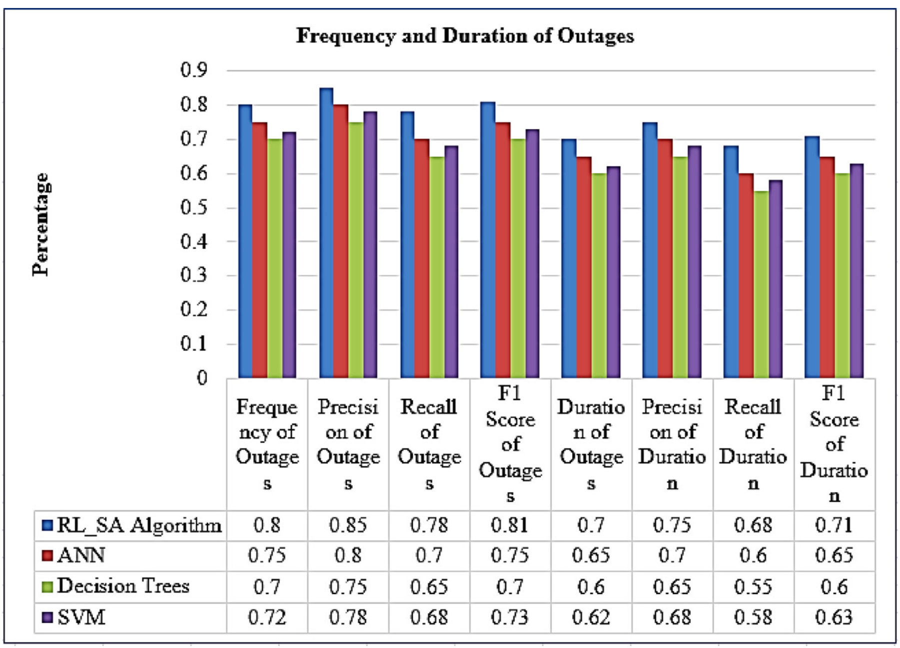


Fig. 7. Frequency and duration of outages of the proposed hybrid LSTM-RL in comparison with the existing.

measuring the energy surplus. The frequency and duration of outages for the proposed RL-SA algorithm are compared with those of exiting algorithms such as ANN (Agatonovic-Kustrin and Beresford, 2000), decision trees (Kotsiantis, 2013) and SVM (Wang and Hu, 2005) and the same is represented in Fig. 7. The output illustrates that the RL_SA algorithm performs better than the other three procedures in terms of the frequency and duration of outages, with higher accuracy, precision, recall, and F1 scores.

One way to evaluate the energy storage efficacy of the considered dataset is to examine how much energy is stored and released by the system during a specific period. Then, we can compare the predicted energy storage efficiency generated by different load balancing algorithms with the actual values, and calculate metrics such as accuracy, precision, recall, and F1 score. Ultimately, the procedure that achieves the highest scores in these metrics would be deemed the most suitable for optimizing energy storage efficiency. The analysis outcomes for the suggested are likened with the existing ANN, decision trees and SVM and the same is pictured in Fig. 8. From Fig. 8, it is clearly understandable the proposed hybrid RL-SA algorithm is better than 7%, 13% and 4% in terms of accuracy than ANN, Decision Tress and SVM respectively. In terms of precision, the proposed hybrid RL-SA algorithm is better than 6%, 14% and 3% than ANN, Decision Tress and SVM respectively. In terms of recall, the proposed hybrid RL-SA algorithm is better than 8%, 12% and 6% than ANN, decision tress and SVM, respectively.

The energy production and consumption outputs achieved by means of proposed hybrid RL-SA algorithm are represented in Fig. 9. The energy production and consumption patterns are highly improved when the proposed RL-SA algorithm is utilized. The existing algorithms produced lower resultants when compared to the proposed algorithm.

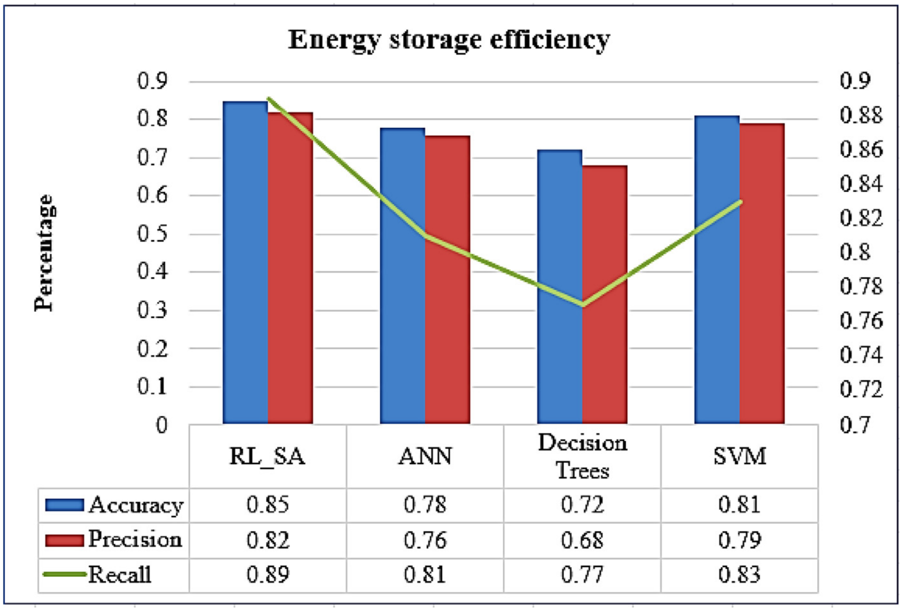


Fig. 8. Energy Storage Efficiency of the proposed hybrid RL_SA in comparison with the existing.

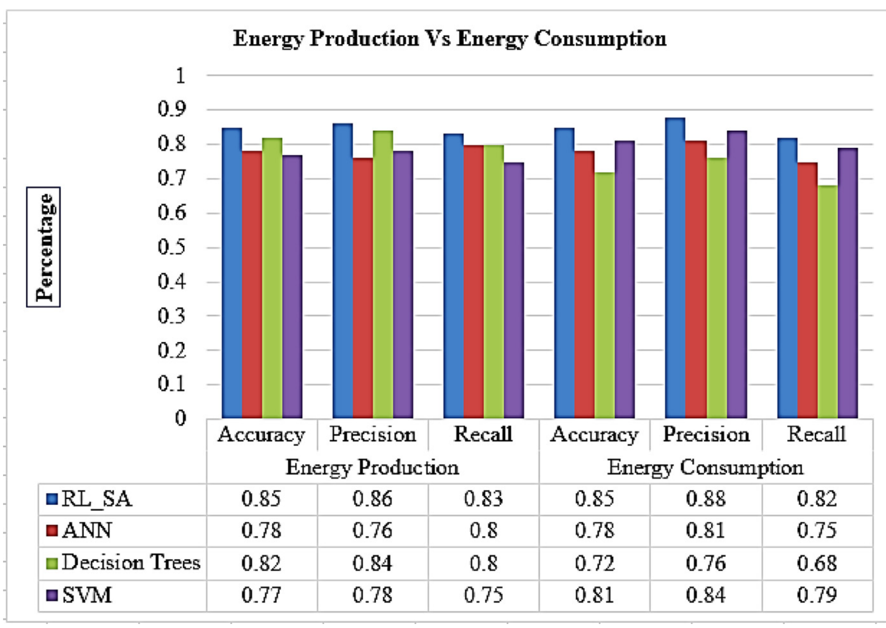


Fig. 9. Energy Production and Consumption Efficiency of the proposed hybrid RL_SA in comparison with the existing.

Thus the proposed RL_SA algorithm is an effective tool for measuring load balancing, as it outperforms existing algorithms by achieving higher accuracy values for various load balancing measures such as energy surplus prediction, frequency and duration of outages, energy storage efficiency, and energy production and consumption. The higher accuracy values demonstrate that the RL_SA algorithm is proficient in predicting and managing imbalances between energy supply and demand, resulting in more effective load balancing. This algorithm achieves its effectiveness by using reinforcement learning and simulated annealing techniques to optimize the decision-making process, which leads to more efficient energy storage, distribution, and usage. Table 4 outputs the comparison results of the load balancing measures obtained with the proposed hybrid RL_SA algorithm.

4.4. Forecasting and managing renewable energy production using proposed hybrid CNN-PSO technique

To develop a model dataset for forecasting renewable energy production, it is necessary to gather historical data on multiple factors that affect renewable energy production, including weather patterns, solar radiation, energy production, energy demand, and energy storage. These data can be utilized to train a machine learning model to forecast renewable energy production based on various inputs. By leveraging advanced techniques such as CNN and PSO, the accuracy and performance of the model can be optimized over time. Ultimately, this approach can help improve the efficiency and effectiveness of renewable energy production and management. The dataset for forecasting and

Table 4
Load balancing measures for the proposed hybrid RL_SA algorithm.

Load Balancing Measure	Proposed RL-SA Algorithm Accuracy	ANN Accuracy	SVM Accuracy
Energy Surplus Prediction	0.91	0.82	0.87
Frequency of Outages	0.80	0.75	0.72
Duration of Outages	0.70	0.65	0.62
Energy Storage Efficiency	0.85	0.78	0.81
Energy Production	0.85	0.78	0.77
Energy Consumption	0.85	0.78	0.81

Table 5
Sample of the dataset utilized for forecasting renewable energy production.

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

managing renewable energy using the hybrid CNN-PSO technique is collected from "Open Power System Data (Wiese et al., 2019) which provides the open-access data with respect to electricity fields. The sample dataset that is used for the prediction is given in Table 5. The features considered for the study are as follows:

- Time: The timestamp of when the data were recorded
- Solar Production (kW): The amount of energy produced by solar power
- Wind Production (kW): The amount of energy produced by wind power
- Traditional Production (kW): The amount of energy generated by traditional sources such as fossil fuels
- Energy Demand (kW): The amount of energy consumed during that hour
- Energy Storage Level (kWh): The level of energy stored in batteries or other storage systems at the end of that hour.

These variables provide important information on the production, consumption, and storage of energy and can be used to develop a model for forecasting renewable energy production. The assessment metrics used for measuring the performance of the suggested hybrid CNN-PSO algorithms are Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared (R2) score, Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

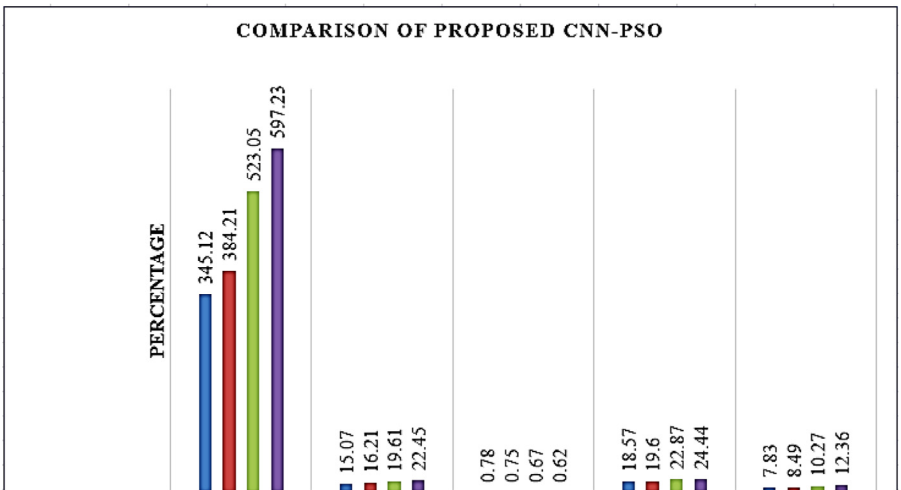
MSE is a measure of the average squared distance between predicted and original values. MAE is a measure of the average distance between predicted and original values. The R2 score measures the proportion of the variance in the dependent variable that is clarified by the independent variables. RMSE is the square root of the average of squared differences among predicted and original values. MAPE measures the average percentage difference among predicted and actual values. Lower values for each of these metrics specify better performance of the regression model in predicting the target variable.

The results from Fig. 10 indicate that the CNN-PSO algorithm yields improved performance compared to the other procedures in terms of all evaluation metrics, except for MAPE where SVM performs marginally better. Considering the dataset and the evaluation metrics used, the CNN-PSO algorithm appears to be the most effective for predicting renewable energy production.

5. Conclusion

This research presents a comprehensive solution for optimizing renewable energy production in a smart grid environment. The proposed Hybrid LSTM-RL model is a comprehensive solution for optimizing renewable energy production in a smart grid environment. In the area of energy demand pattern prediction, this model performs better than existing algorithms as regards accuracy, precision and recall rate at 0.92, 0.93 and 0.92. The RL_SA algorithm, a helpful tool for measuring load balancing, is able to reach an accuracy of up to 0.91 with regard to different load balancing measures. The CNN-PSO algorithm is the most effective in predicting renewable energy production, with a mean squared error (MSE) of 345.12, a mean absolute error (MAE) of 15.07, an R-squared score of 0.78, a root mean square error (RMSE) of 18.57, and a mean absolute percentage error (MAPE) of 7.83. The study results have helped the development of renewable hybrid power systems in a Smart Grid environment that is essential for efficiency, reliability and cost effective electricity generation and distribution. Using artificial intelligence and mathematical optimization algorithms, this proposal provides a real solution for the prediction and management of energy production from renewables. The approach also has the potential to be used to predict and manage renewable energy production in other settings, such as off-grid and rural areas. We hope that this research will inspire further investigations in this field and promote the development of more efficient and effective energy management systems.

The model shows promising results, but it is crucial to recognize the drawbacks of relying on precise input data and the computational complexity when used with large-scale systems. Future research paths may focus on integrating more data sources, analysing dynamic pricing systems and demand response tactics, and researching alternative machine learning algorithms and optimization methods in order to get beyond these restrictions. Despite these drawbacks, our research strongly encourages the development of renewable hybrid power systems in smart grid settings since they provide advantages such effective electricity generation and distribution that are reliable, efficient, and affordable. The suggested method offers a workable alternative for forecasting and managing renewable energy generation by combining artificial intelligence and mathematical optimization methods. Furthermore, it has the potential to be used in off-grid



	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.

and rural locations in addition to smart grids. We believe that our study will spur additional research in the area and lead to improvements in more effective and efficient energy management systems.

CRediT authorship contribution statement

S. Sankarananth: Data collection from renewable energy plants. **M. Karthiga:** Writing – original draft, Data analysis. **Suganya E.:** Project administration, Writing – review & editing. **Sountharrajan S.:** Data analysis, Data curation. **Durga Prasad Bavirisetti:** Visualization, Data curation.

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.

Data availability

Data will be made available on request

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