Ibn Al-Haitham Journal for Pure and Applied Sciences
Journal homepage: jih.uobaghdad.edu.iq
PISSN: 1609-4042, EISSN: 2521-3407
IHJPAS. 2024, 37(4)

The Intelligent Data Analysis Techniques and its Significant Impact on Managing Renewable Energy Resources

Ghada S. Mohammed[1,*], Osama Basil Ghazi [2], Ahmed Basil Ghazi[3] and Salahuddin I. Abdrabba[4]

[1, 2]Department of Computer Engineering Techniques, Madenat Alelem University College, Baghdad, Iraq.
[3]Department of Computer, College of Education For Pure Science (Ibn Al-Haitham), University of Baghdad, Baghdad, Iraq.
[4]Department of Electrical and Electronic Engineering, University of Omar Al_Mukhtar, Al-Bayda, Libya.
* Corresponding Author.

Received: 17 February 2024 Accepted: 5 May 2024 Published: 20 October 2024
doi.org/10.30526/37.4.3922

Abstract

Accelerated technological development has a significant role in highly increasing energy demand, which enhances the interest of companies and governments in adopting renewable energy sources and finding new technologies that enable the effective use of these sources, such as techniques for predicting the amounts of generated and consumed energy, technologies of energy storage, and others. The high complexity of energy networks also necessitates intelligent systems to manage energy production and distribution with high efficiency, which is based on intelligent data analysis techniques. This paper conducts a comprehensive analysis of the critical impact of intelligent data analysis techniques (Deep Learning and Machine Learning) in the management of renewable energy systems. Machine learning uses previous data to forecast and optimize energy production and consumption. While deep learning excels at dealing with complex connections and non-linear patterns, The analysis showed that using and developing these technologies in renewable energy applications improves decision-making processes by providing more accurate predictions, highly efficient resource usage, minimizing complexity in the computations and time of system implementation, and creating robust renewable energy systems with minimum cost. As the renewable energy sector grows, combining Deep Learning (DL) and Machine Learning (ML) will be critical to encouraging efficient investment and intelligent management practices in renewable energy and sustainability applications.

Keywords: Renewable energy, Intelligent data analysis, Deep learning, Machine learning, Green energy.

1. Introduction

Recently, the world has witnessed an increasing energy crisis, which coincided with the rapid economic recovery following the slowdown caused by the spread of the Corona pandemic

(COVID-19). However, this situation was viewed as an opportunity to introduce renewable energy sources into the market. There is a growing need to encourage the creation of ambitious projects aimed at managing renewable energy and making optimal investments in it. Therefore, there is an accelerating trend toward using data analysis techniques that can do this. Intelligent data analysis techniques help to manage the use of renewable energy by increasing the efficiency of energy management systems and improving their use. Increasing the capabilities of smart networks for energy generation and distribution in response to the anticipated future increase in energy demand results in cost savings, reduced environmental impact, and a reduction in carbon emissions and their impact on the climate and human health. This paper produces a general comparative analysis of different research on Renewable Energy (RE) management systems based on the intelligent analysis techniques (IDA) used in these studies. The comparative analysis in this study divided the research into three groups: the first one is the research that used IDA techniques in renewable energy forecasting and illustrated the role of these techniques in obtaining good results in the proposed renewable energy systems; the second one illustrated the IDA techniques dealing with surplus renewable energy and the role of them in dealing appropriately with the surplus energy; and the last group illustrated the IDA techniques that were used to determine the feasibility of the systems of renewable energy and the result that helped in making a decision in initializing such systems (as shown in **Figure 1).** We prepare the remaining sections of this study as follows: In Section 2, the main concept of Renewable Energy is briefly introduced. Section 3 illustrates the IDA techniques and their main steps. Different types of IDA are also illustrated in this section. The comparative analysis of IDA techniques in the management of renewable energy takes place in Section 4, while the final section presents the main conclusions drawn from this study.

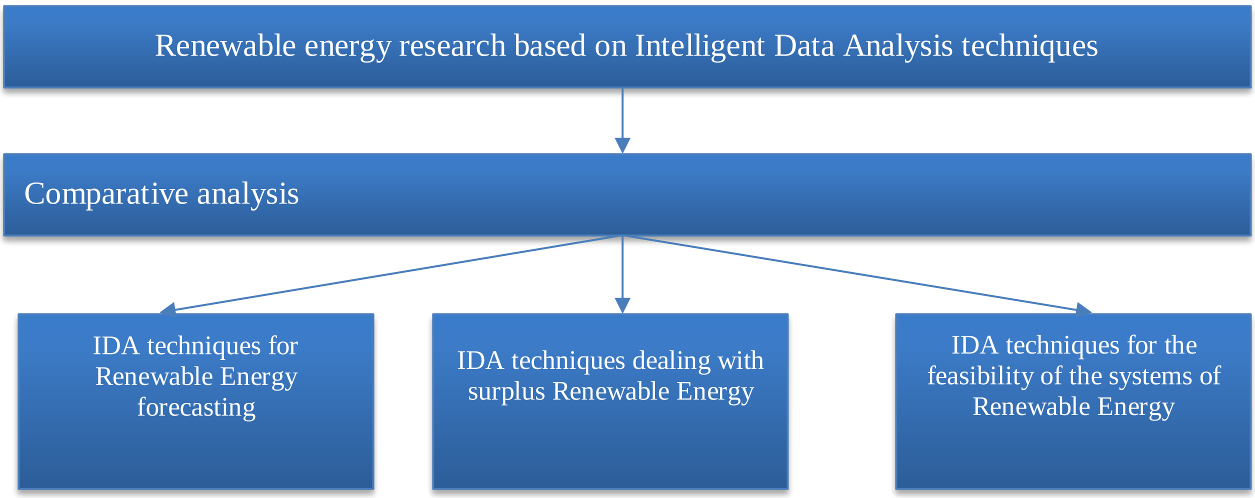

Figure 1. The main research groups used in this study

2. Renewable Energy (RE)

RE is environmentally friendly energy or green energy that has little environmental effect; this energy is generated from natural sources that provide vast quantities of energy and can renew spontaneously. The sources of RE include ocean waves, hydropower, biomass from photosynthesis, wind power, and direct solar energy. Environmentally friendly energy offers several advantages, such as being non-polluting, sustainable (one-time installation), affordable, omnipresent, safe, and giving a diverse variety of possibilities; yet, some of the sources have disadvantages (such as being more expensive or having an environmental effect) [1].

Types of solar energy: sunlight and solar thermal radiation are two forms of energy generated naturally; solar radiation is the most cost-effective and efficient energy source. Two principal solar-energy collection technologies are solar thermal collectors and photovoltaic cells. The main factors affecting solar energy systems are climatic ones (air temperature, humidity, cloudiness, and solar radiation), as well as the state of the system itself (radiation, dust, and so on). Yet there is a direct relationship between these parameters and the power produced, so it would be better to develop models that can describe the behavior of such systems in as reliable and accurate a way as possible [2].

Wind energy systems generate electricity by transferring the kinetic energy of air flows to electric power via a generator. We classify wind turbines into two types: horizontal-axis wind turbines and vertical-axis wind turbines. This technology has reached a good state of maturity and is cost-competitive. However, wind turbines have significant drawbacks, such as noise pollution, vibration fatigue failure due to turbulence, and concerns about animal welfare. They also have a high failure rate of 3–5% annually [2, 3].

Hydropower plants, among the oldest methods used to generate electricity, are relatively simple in their processes. This renewable energy source boasts the highest efficiency to date. The efficiency of large hydropower systems can reach nearly 95% due to economies of scale, optimized infrastructure, and advanced turbine technology. While still efficient, small systems may get around 85% efficiency due to limitations in scale, turbine size, and maintenance resources. Because the process of converting potential energy into electric power is much more straightforward than any other form of renewable energy, these systems are among the most economical ways to generate clean energy [4, 5].

Generally, the type of energy system and its components dictate the appropriate energy management strategy. In light of this, researchers employed various strategies and techniques, including intelligent data analysis, to formulate an effective energy management plan [5].

Renewable energy management has many essential features, such as resource evaluation, system design and integration, energy storage solutions, smart grid technology, grid development, grid stability and balance, energy management software, lifecycle assessment, maintenance, and optimization [6].

3. Intelligent Data Analysis (IDA)

IDA is a subfield of modern science that involves finding out the most valuable facts through data science to specify and solve significant problems step-by-step; then, its solutions must be accessible to all persons and expressed without particular expertise or insider knowledge. The IDA involves the following steps:

- Collecting the data that describes a real problem and transforming it into an appropriate form for analysis.
- A model based on examination-relevant data characteristics preparing and preprocessing the data to solve real problems.
- Deep learning and machine learning techniques are used to analyze data and create comprehensible patterns.

Many different types of energy-related problems have been solved successfully with intelligent data analysis techniques, such as those incorporating data mining and statistical or machine learning algorithms, including forecasts of renewable energy generation and forecasts of energy consumption (e.g., sun Irradiance) [7]. Because of the intelligent data analysis techniques' capacity to handle vast amounts of data and find complicated patterns, they are great tools for extracting meaningful insights from disparate datasets.

ML and DL are significant disciplines of AI (as shown in **Figure (2)**). ML algorithms are developed on a wide range of data and prove highly efficient in dealing with data heterogeneity and complex forecasting challenges [8, 9]. DL has multiple layers capable of developing properties at a high degree of abstraction [10]. These algorithms may be executed automatically, removing the requirement for human intervention collecting the data that describes a real problem and transforming it into an appropriate form for analysis.

- A model based on examination-relevant data characteristics preparing and preprocessing the data to solve real problems.
- Deep learning and machine learning techniques are used to analyze data and create comprehensible patterns.

Intelligent data analysis techniques, which incorporate data mining and statistical or machine learning algorithms, have successfully solved many different types of energy-related problems, including forecasts of renewable energy generation and energy consumption (e.g., sun irradiance). Because intelligent data analysis techniques have the capacity to handle vast amounts of data and find complicated patterns, they are excellent tools for extracting meaningful insights from disparate datasets.

Figure 2 illustrates the significance of ML and DL as disciplines within AI. We develop ML algorithms on a wide range of data and find them highly efficient in handling data heterogeneity and complex forecasting challenges. DL has multiple layers capable of developing properties at a high degree of abstraction [10]. Automated execution of these algorithms eliminates the need for human intervention [9].

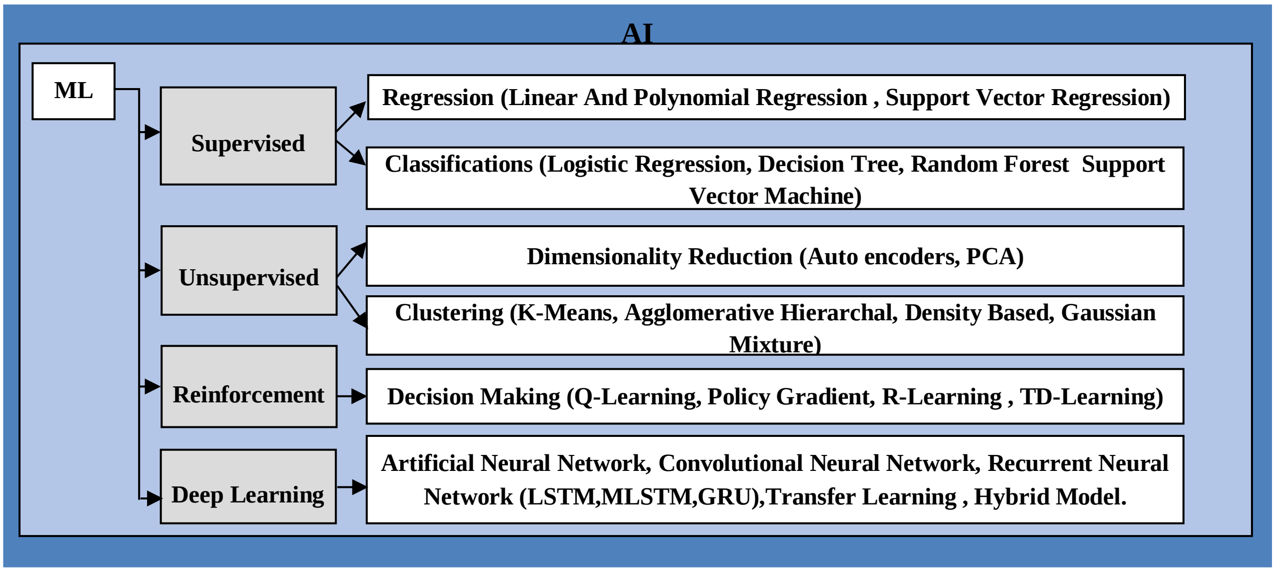

Figure 2. Types of ML techniques and the relation between (AI, ML, and DL) [8]

The depth of the network is determined by the number of layers, and each layer consists of a different number of neurons with one or many types of activation functions. DL has many advantages, such as its ability to handle complex types of data without user instruction and scalability. While DL models may be expensive to develop, they produce high-quality results that are beneficial for organizations. Studies [11, 12] have noted the benefits of deep learning. DL poses several challenges, such as the requirement for a substantial amount of training data to achieve a well-performing model. DL models are also very complicated and need a lot of memory. Even small changes to the model can produce different outcomes because it is not fully described; also, issues with vanishing or exploding gradients can stop the proper updating of weights, which can make models unstable [8].

4. Comparative Analysis of IDA Techniques in the Management of Renewable Energy

Much recent research in renewable energy management has concentrated on building comprehensive techniques for successfully harnessing sustainable energy sources. Researchers are conducting research to enhance the integration of renewable energy technologies like solar, wind, and hydropower into the existing energy infrastructure. To handle the intermittent nature of renewable energy sources, researchers stress resource evaluations, system design, and seamless integration of energy storage systems. This study primarily concentrates on the challenges encountered by renewable energy applications and the methods employed; we present a selection of these studies below, each from a unique perspective on their application.

4.1 Intelligent data analysis techniques for renewable energy forecasting

Much research is based on using IDA techniques to forecast many factors related to renewable energy, such as the maximum amount of generated energy, surplus energy, the demand for energy, consumption of energy, and many others. Table 1 provides an illustration of some of the research findings.

Kumar & Saravanan presented a method to predict the demand for renewable energy (solar, wind) and non-renewable energy (diesel generator and fuel cell) based on fish swarm optimization techniques. The proposed method is used to manage the load of energy, sources, and storage [13].

Kaabeche & Bakelli developed a unique energy generation system (wind and sun) for Algeria, which was implemented using a storage device. The system's future performance is projected by considering the impact of lifespan, the relative cost of batteries, and depth of discharge (DOD) technologies. The JAYA approach creates output that is more likely to result in optimum solutions than other algorithms [14].

In order to deal with the periodicity of time series with multiple variables of data, Wang et al. proposed a prediction model that relies on pre-processing data, analyzes its periodicity, and uses a Many Convolutions neural network (CNN) [15]. This model significantly outperforms ConvLSTM.

Agada et al. developed a two-state Markov Chain model to predict the chance occurrence of surplus and deficit net radiation for one year in Ibadan, Nigeria. When you look at the monthly transition counts, transition probability matrix, n-step transition matrix, steady state probability vector, and vector of mean reoccurrence times for the two states to figure out the net radiation, you can see that the chances of there being too much net radiation going on go up some months and down others [16].

Haidar et al. provide a more efficient method for analyzing the functioning of multiple hybrid microgrid systems and implementing the hybrid system in Long San Village, Sarawak, Malaysia. Based on multi-objective particle swarm optimization and a range of meteorological circumstances, they provide a mathematical model that supports a maximum load demand at the lowest cost. We evaluate the system's function by assessing its dependability and voltage security, and conducting numerous system examinations [17].

Chen & Chang proposed a preprocessing technique for forecasting solar energy based on the Pearson coefficient. The LSTM technique is used to build the predictor, reducing the influence of disturbances on the solar energy forecast and achieving short-term solar energy prediction [18].

Qu et al. introduced a hybrid prediction model for distributed PV energy. The parameter and resolution adaptive technique prepares the data before employing the distributed GRU model to find daily patterns of fluctuation for the solar power series. Compared to traditional numerical weather forecasting methods, the model provides adequate forecasting accuracy and effectiveness [19].

Luo et al. suggested a precise PV energy generation prediction approach that utilized deep learning methodologies, real-time PV, and knowledge of the field to account for particular engineering challenges to boost efficiency and precision [20].

Pan et al. suggested a technique for predicting solar generation intervals using GRU with kernel density estimation. When applied to multiple datasets and pre-processed to put them into this model, the model beats other competing approaches; the model may need to be updated and evaluated over lengthy periods [21].

Jebli et al. proposed a method for predicting solar energy based on machine learning and deep learning techniques. The usefulness of the investigated models for real-time and short-term solar power prediction was evaluated to ensure optimum management as well as security criteria in this sector while employing an integrated approach constructed around a single tool and an appropriate prediction model [22].

Liu et al. suggest a framework for integrating the benefits of multiple methods with the suggested ensemble forecasting frame depending on optimization, statistical, and DL techniques for precise and reliable photovoltaic power predictions in Belgium, using various datasets and evaluating many indicators [23].

Khan et al. suggested a DSE-XGB stacked ensemble technique for reliable solar power prediction that integrates artificial neural networks, extreme gradient boosting, and extended short-term memory techniques [24].

Wang et al. introduced the PV prediction technique, which relied on a statistical method with LSTM to predict energy. Compare numerous approaches (Stacked-LSTM, LSTM-SVR, SVR, GRU, Backpropagation NN, and LSTM-SVR-Bayesian optimization models). With excellent prediction accuracy, the proposed technique beats the other models [25].

Al-Ali et al. employed a mixture of CNN and LSTM approaches to forecast solar energy. They also used a clustering methodology to preprocess the data and analyze the correlation among the input data. They utilize the fingered dataset to provide short-term forecasting energy findings [26].

Table 1. Comparative analysis of IDA in renewable energy forecasting

Author	Energy source	Methodology	Aim of application	Results
[13]	Solar wind	Make data in muli-model (generator, load, cost, uncertainty of energy and storage), Artificial fish swarm optimization techniques.	Prediction of demand for renewable energy and non-renewable. Energy (diesel generator, fuel cell) manages the load of energy, source, and storage.	Optimize the energy generation cost by using IDA techniques, where the suggested algorithm is effective in scheduling the energy need between generators in inverse relation to their cost of production, the proportion of energy available from generators is 100% for renewable power plants, 93.97%/97.02% for diesel generators, 88.72%/93.11% for microturbines, and 88.91%/71.65% for fuel cells.
[14]	PV WT	Sensitivity analysis ant lion, grey wolf, krill herd, and JAYA algorithms	Determine a seasonal average consumption with different configurations.	IDA techniques improve the prediction system performance, (The findings demonstrate the superiority of JAYA, which converges towards the best outcomes for different types of batteries (95% of runs for Lithium-ion, 98% for Lead-Acid, and 100% for Nickel Cadmium), which is not the case for other methods.)

[15]	Solar	Multiple CNN	Solar prediction	Periodic examination of data. The outcomes of Multiple CNNs show the Root Relative Squared Error equal to RSE 0.1915
[16]	Historical solar irradiation data.	Penman-Monteith (FAO-56) approach, Two-state Markov Chain model.	Predict the likelihood of positive and negative net radiation.	The use of IDA methods helps determine where there is a 69%, 76%, 76%, 74%, 63%, 63%, 70%, and 52% chance that net radiation will be surplus in February, March, April, May, June, October, November, and December and a 54%, 64%, 76%, and 55% chance that it will be deficit in the beginning of January, July, August, and September, respectively.
[17]	Hybrid energy systems	HOMER & PSCAD software, Combined (MOPSO & regression method).	Dynamic price estimation	The outcomes of the simulations reveal that the precise dynamic energy price is reached by employing the stochastic optimization technique, which deals with system uncertainties in terms of sources of renewable energy and load demand.
[18]	Solar	LSTM, Pearson feature selection	Predicting solar energy.	IDA techniques reduce the influence of noise on PV and perform short-term forecasting tasks for solar energy, where LSTM reaches 0.189 Mean Absolute Error and 0.121 Root Mean Square Error.
[19]	Distributed PV.	Distributed GRU, Parameter &Resolution Adaptive algorithm, identify the structure OF cluster.	Forecasting PV-generated energy.	Using IDA approaches improves prediction accuracy for daily variation values for solar energy, with a standardized root mean squared error of 6.83% and a normalized mean absolute error of 4.12%. The most accurate daily standardized mean absolute error and standardized root mean squared error may be as low as 2.75% and 4.58, respectively, which verifies that the suggested day-ahead forecasting model has attained the accuracy level compared to the numerical weather prediction-based day-ahead forecasting models.
[20]	PV	Feature construction, Data normalization, PC-LSTM techniques	Prediction of PV-generated energy.	Accurate photovoltaic energy generation by using IDA approaches where the MAE*10^{-2} equal to 2.95 , MSE10^{-2} equal to4.26, and R^2 score equal to 0.910
[21]	Solar	Analysis of probability, GRU Algorithm & KDE	Prediction intervals of solar generation.	High accuracy prediction intervals of solar generation where the MAE is 0.1158, RMSE is 0.2683, and A-GRU forecast skill is 0.2522
[22]	Solar	Data Filtering, Pearson Correlation, Random Forest Algorithm and MLP	Forecasting Solar Energy.	Short-Term Solar Energy Forecasting by using ANN with an accuracy of up to 93%
[23]	PV	Clustering technique, optimization, statistical, and DL Techniques	PV energy forecasting	The IDA technique used in the suggested forecasting framework yielded MAPE scores of less than 2, 3, and 5%, respectively, outperforming previous models in terms of stability and efficiency. It improves solar power forecasting performance and serves as an effective tool for intelligent grid planning.
[24]	Solar	Data Cleaning DSE-XGB Stacked Ensemble Method	Prediction of Generated Energy	Prediction of Maximum Generated Energy with Good Accuracy reached 95% and 94% in different cases.
[25]	PV	LSTM, Statistical methods	PV power Prediction	The results and comparative analysis show that the hybrid LSTM-SVR-BO method can achieve superior forecasting performance in predicting the energy generated across several short-term periods.
[26]	Solar	Clustering technique Combination of CNN and LSTM	Forecasting only short-term generation energy	The proposed model's IDA demonstrated the maximum accuracy. The findings indicate that the suggested model is a reliable forecasting tool for integrating solar energy into networks. The suggested model obtained the lowest RMSE and MAE values, 0.344 and 0.393, respectively.

Table 1 illustrates a comparative analysis of the results obtained in various types of research. The comparative analysis showed that the IDA techniques achieved good results that helped improve decision-making processes by providing more accurate predictions. These predictions play a crucial role in managing various renewable energy systems.

4.2 Intelligent data analysis techniques dealing with surplus Renewable Energy

Much research is based on using intelligent data analysis techniques to deal with the surplus of renewable energy with or without storage; the surplus of renewable energy results from the availability of factors that increase the amount of generated energy, such as weather factors and specific equipment to manage the generation of this energy. Table 2 illustrates some of these research findings:

Chaouachi et al. proposed a system to predict renewable energy, which includes multiple resources, such as solar and wind, using an artificial neural network. This system utilized a fuzzy expert system for battery scheduling and load demand, resulting in a reduction in overall operational costs [27].

Fu et al. presented a strategy to optimize the allocation method of routing and dynamic storage based on reinforcement learning (vehicular energy network with LSTM); this strategy increases the efficiency of energy transfer [28].

Zang et al. introduced a model of real-time dynamic energy management for Hybrid Energy Systems (HES). They utilized a Deep Reinforcement Learning algorithm to determine the strategy in terms of investment and input on different supply sides based on historical data, including time factors such as Power system Heat Rate Aggregation (PSHRA). PPO is a proximal optimization policy based on training with different types of data. According to the results, the optimal control policy and costs decreased by 14.17% [29].

Mohammed et al. proposed a multi-agent system based on heuristic optimization principles designed to efficiently store excess energy from various renewable energy sources. The system's performance was checked in five regions and 12 cities in Iraq. The results from the system illustrate how high supplier rates increase electricity exchange and affect production planning for various RE sources, as well as optimizing the use of storage devices at different locations [30].

Yuan et al. presented a solution to store renewable energy surpluses. This solution assisted in conserving energy for future investment into various applications. This solution is based on using a deep reinforcement learning technique and regulating policies to deal with the dynamic energy demand. Also, this model contributes to reducing the cost of renewable energy generation [31].

Al-Janabi and Mohammed came up with a way to figure out how much extra energy there is by using the Find Different Intervals of Renewable Energy (FDIRE) method and combining data from RELSTM techniques to figure out what kind of solar plant makes the most electricity [32].

Table 2 illustrates the results of using the IDA techniques to deal suitably with the surplus generated renewable energy and exploit it without loss. This helped manage the renewable energy system optimally.

Table 2. Comparative analysis of IDA in dealing with surplus renewable energy

Author	Energy source	Methodology	Aim of application	Results
[27]	Solar Wind	Artificial Neural Network ensemble, fuzzy expert system	Minimize operational costs and reduce the impact of emissions on the environment	Reduced the operational cost of the grid; according to the simulation, the cost savings of the suggested IDA strategy compared to opportunity charging were 4.63% against 8.15% as a result of intelligent battery scheduling that considers the next day's solar energy availability.
[28]	Solar	LSTM Concept of reinforcement learning	Optimize routing and dynamic allocation of storage	Near to high efficient performance, where outcomes indicate that combined optimization with an LSTM model achieves a dynamic storage allocation and maximum energy flow with RMSE(cars) MAPE(%) of 167.8 and 1.68%, respectively.
[29]	WT Solar Diesel generator Battery	Deep reinforcement learning algorithm, MULTI-objective adaptive algorithm.	Control the RE system by reducing its cost.	Obtain the best energy management strategy. Simulation findings show that a well-trained agent may deliver a better control policy and lower expenses by up to 14.17% when compared to alternative techniques.
[30]	Solar WT Hydropower.	Handling and Analysis of various energy loading curves of consumption behaviour in five regions / IRAQ.	Multi-agent-based heuristic optimization system	Optimal utilization of located storage devices. Determine the energy demand for a specific city. The study analyzed the impact of varying the number of suppliers and distributors in each location (five regions and twelve cities).
[31]	Solar Wind	Dynamic real-time update of parameters, Deep reinforcement learning	Maximize the utilization of RE and reduce the cost.	Improve decision-making efficiency. According to trial data, the proposed system reduces costs by 74.8% throughout the billing cycle and enhances renewable energy consumption.
[32]	Solar	FDIRE RELSTM	Determine the type of solar plant and Predict the amount of solar-generated energy. Compute the amount of surplus energy.	By determining only different intervals of energy, we can reduce the complexity of computations and time spent on energy generation, increase efficiency, and increase the accuracy of the IDA used.

4.3 IDA techniques for the feasibility of the systems of renewable energy

Many studies rely on intelligent data analysis techniques to evaluate the viability of investing in various forms of renewable energy in different locations. These studies consider a variety of factors related to the implementation of renewable energy projects, as well as the development of specific models to support these projects. These factors include computation complexity and implementation time, as well as performance accuracy and efficiency. Table 3 illustrates some of this research.

Kharrich et al. evaluated the practicality of constructing a microgrid system using a combination of hybrid renewable energy sources. They compared three different kinds of optimization algorithms and used a sensitivity analysis to determine which was the most successful. The better algorithm, as stated in the results, is SPEA2 (Strength Pareto Evolutionary Algorithm) [33].

Oryani et al.'s colleagues found various barriers to power source development and classified them into five categories. The low-quality scores of biomass and wind turbines, two significant sources of sustainability currently in use, may prompt me to reassess my overall evaluation scheme [34].

Fares et al. examine the efficiency of ten distinctive metaheuristic optimization techniques used to decrease the total cost. The simulation results show that the flower pollination and simulated annealing techniques have high accuracy, and the flower pollination algorithm has an efficient execution time. The best performance techniques were Brainstorm optimization in the objective space algorithm and SA, followed by Firefly optimization. Simulated Annealing is the most successful solution to the HRE system scaling problem [35].

Table 3. Comparative analysis of IDA in the feasibility of RE applications

Author	Energy Source	Methodology	Aim of application	Results
[33]	PV. WT. Diesel generator. Battery.	Determine Objective functions and Constraints. Strength Pareto, Evolutionary Algorithm (SPEA2)	Sensitivity analysis includes functions for normalizing production costs, reducing emissions, and improving the efficiency of a system.	The suggested hybrid microgrid system is cost-effective, dependable, and provides electricity for over 98% of the time at a reasonable cost.
[34]	PV. WT. Biomass.	Ensemble forecasting frame Sensitivity analysis	Determine and assign priority to the significant barriers to RE.	Determine the percentage of challenges in improving PV, WT, and biomass. In Iran, solar PV has the lowest development obstacles (0.212), followed by wind turbines (0.364) and biomass (0.424). Solar PV has fewer development constraints than wind turbines and biofuels.
[35]	PV. WT.	System component description and modelling Ten distinct metaheuristic optimization methods.	Reduce the system's entire Net Present Cost, Maintaining an acceptable power supply shortfall probability.	Using the IDA techniques contributes to reducing TNPC in comparison to ideal solutions. FPA and SA are pretty efficient.
[36]	PV. Hydrogen-diesel. PV. Battery-diesel.	Handling a combination of data, HOMER Pro 3.15 software	Determine the feasibility of the economic and technical advantages of RE	Determine that the configuration with hydrogen storage was less cost-effective than the traditional
[37]	Wind. Solar. Biomass. Hydropower.	Statistical method. Machine learning.	Feasibility study of investment in RE taking into consideration many factors.	IDA techniques help in making the best decision to invest in renewable energy (The maximum accuracy was 0.94. The minimum and highest MSE for biomass technology and hydropower technology were 0.058 and 0.771, respectively. Furthermore, the energy generation risk from RET and the electricity pricing risk in each nation are the most crucial elements for deciding on RET investment.)

Yaïci et al. proposed a model through their study to demonstrate the viable use of hybrid renewable energy resources along with hydrogen techniques and batteries for supplying power to remote houses. To increase the efficiency of the fundamental microgrid systems, researchers used HOMER Pro Software to design a model that employs artificial techniques. Analysis demonstrates the usefulness of PV cells, whether connected to batteries or hydrogen and diesel systems, for rural electrification [36].

Izanloo et al. proposed a method that combines machine learning and statistical methods to make a decision related to investment in the RE based on many factors, such as the price of energy, its generation, and energy demand [37].

Table 3 illustrates an analysis of comparatively different techniques used to determine the feasibility of initiating renewable energy systems in different locations. This will help in making a good decision in the field of sustainable energy.

5. Conclusion

The using of IDA techniques for renewable energy management represents an important step forward in creating more resilient, efficient, and sustainable energy systems, as these technologies provide significant contributions in a variety of areas, from accurate energy forecasting and load balancing to grid stability and fault detection. The ability of machine learning techniques to examine previous data for predictions, in addition to the efficiency of deep learning in managing precise correlations in large data sets, increases the efficiency of the systems by increasing the accuracy of the results and reducing the complexity of time and calculations in these systems at the same time, thus reducing the cost of these systems, which leads to enabling the Decision makers to improve energy production, distribution, and consumption. The implementation of these cutting-edge technologies has the potential to usher in a new era of robust, responsive, and environmentally responsible energy management technologies as the renewable energy industry evolves. As a result, the use of intelligent data analysis techniques for renewable energy management can:

1. IDA techniques have a vital impact on the renewable energy field.
2. Improve and enhance the efficiency of applications by increasing the accuracy of obtained results.
3. Reduce the complexity of implementation time by accelerating the computations.
4. Optimize the decision-making related to many factors associated with renewable energy, such as the storage of surplus energy or investment in it in a different manner.
5. Real-time management of renewable generation energy systems.
6. Increase the ability of predictive analytics for renewables, which includes identifying areas with the highest potential for AI in renewable energy development, such as solar panels and wind, also predicting the amount of generated energy, amount of consumed energy, amount of energy demand, amount of surplus energy, and fluctuation of energy during the year, also predicting the impact of weather factors in the generation the energy, and many other factors, Through comprehensive analytics, suppliers can benefit from artificial intelligence to produce energy efficiently
7. Finding a vast range of opportunities to invest in the field of renewable energy.
8. By monitoring the patterns of data and trends, IDA techniques can identify potential problems before they occur, ultimately allowing corrective actions to be taken to avoid disruptions.

Acknowledgment

The authors greatly appreciate the referees for their valuable comments and suggestions for improving the paper.

Conflict of Interest
The authors declare that they have no conflicts of interest.

Funding
There is no financial support in preparation for the publication.

References

1. Baydyk, T.; Kussul, E.; Wunsch Ii, D.C. *Intelligent automation in renewable energy*. Springer International Publishing, Springer Cham, **2019**. https://doi.org/10.1007/978-3-030-02236-5
2. Rangel-Martinez, D.; Nigam, K.; Ricardez-Sandoval, L.A. Machine learning on sustainable energy: A review and outlook on renewable energy systems, catalysis, smart grid and energy storage. *Chemical Engineering Research and Design* **2021**, *174*, 414–441. https://doi.org/10.1016/j.cherd.2021.08.013
3. Wu, B.; Lang, Y.; Zargari, N.; Kouro, S. *Power Conversion and Control of Wind Energy Systems*; Wiley-IEEE Press: Hoboken, NJ, USA, 2011; Chapters 1–15; p. 480. https://doi.org/10.1002/9781118029008
4. Breeze, P. Power System Energy Storage Technologies. In *Power Generation Technologies*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 219–249. ISBN 978-0-08-102631-1.
5. Rathor, S.K.; Saxena, D. Energy management system for smart grid: An overview and key issues. *International Journal of Energy Research* **2020**, *44*, 4067-4109. https://doi.org/10.1002/er.4883
6. Olatomiwa, L.; Mekhilef, S.; Ismail, M.S.; Moghavvemi, M. Energy management strategies in hybrid renewable energy systems: A review. *Renewable and Sustainable Energy Reviews* **2016**, *62*, 821-835. https://doi.org/10.1016/j.rser.2016.05.040
7. Mohammed, G.S.; Al-Janabi, S.; Haider, T. A comprehensive study and understanding—A neurocomputing prediction techniques in renewable energies. In *International Conference on Hybrid Intelligent System* **2022**, Cham, Springer Nature Switzerland, 152-165. https://doi.org/10.1007/978-3-031-27409-1_14
8. Benti, N.E.; Chaka, M.D.; Semie, A.G. Forecasting Renewable Energy Generation with Machine Learning and Deep Learning: Current Advances and Future Prospects. *Sustainability* **2023**, *15(9)*, 7087. https://doi.org/10.3390/su15097087
9. Mahdi, G.; Mohammed, S.F.; Khan, M.K.H. Enhanced Support Vector Machine Methods Using Stochastic Gradient Descent and Its Application to Heart Disease Dataset. *Ibn AL-Haitham Journal For Pure and Applied Sciences* **2024**, *37(1)*, 412-428. https://doi.org/10.30526/37.1.3467
10. Medina-Salgado, B.; Sánchez-DelaCruz, E.; Pozos-Parra, P.; Sierra, J.E. Urban traffic flow prediction techniques: A review. *Sustainable Computing: Informatics and Systems* **2022**, *35*, 100739. https://doi.org/10.1016/j.suscom.2022.100739
11. Mijwil, M.M.; Shukur, B.S. A scoping review of machine learning techniques and their utilisation in predicting heart diseases. *Ibn AL-Haitham Journal For Pure and Applied Sciences* **2022**, *35(3)*, 175-189. https://doi.org/10.30526/35.3.2813
12. Sarker, I.H. Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. *SN Computer Science* **2021**, *2*, 420. https://doi.org/10.1007/s42979-021-00815-1
13. Kumar, K.P.; Saravanan, B. Day ahead scheduling of generation and storage in a microgrid considering demand Side management. *Journal of Energy Storage* **2019**, *21*, 78-86. https://doi.org/10.1016/j.est.2018.11.010
14. Kaabeche, A.; Bakelli, Y. Renewable hybrid system size optimization considering various electrochemical energy storage technologies. *Energy conversion and management* **2019**, *193*, 162-175. https://doi.org/10.1016/j.enconman.2019.04.064

15. Wang, K.; Li, K.; Zhou, L.; Hu, Y.; Cheng, Z.; Liu, J.; Chen, C. Multiple convolutional neural networks for multivariate time series prediction. *Neurocomputing* **2019**, *360*, 107-119. https://doi.org/10.1016/j.neucom.2019.05.023
16. Agada, I.; Udochukwu, B.; Sombo, T. Predicting the occurrence of surplus and deficit net radiation in Ibadan, Nigeria. *Science World Journal* **2019**, *14(2)*, 4-11.
17. Haidar, A.M.; Fakhar, A.; Helwig, A. Sustainable energy planning for cost minimization of autonomous hybrid microgrid using combined multi-objective optimization algorithm. *Sustainable Cities and Society* **2020**, *62*, 102391. https://doi.org/10.1016/j.scs.2020.102391
18. Chen, H.; Chang, X. Photovoltaic power prediction of LSTM model based on Pearson feature selection. *Energy Reports* **2021**, *7*, 1047-1054. https://doi.org/10.1016/j.egyr.2021.09.167
19. Qu, Y.; Xu, J.; Sun, Y.; Liu, D. A temporal distributed hybrid deep learning model for day-ahead distributed PV power forecasting. *Applied Energy* **2021**, *304*, 117704. https://doi.org/10.1016/j.apenergy.2021.117704
20. Luo, X.; Zhang, D.; Zhu, X. Deep learning based forecasting of photovoltaic power generation by incorporating domain knowledge. *Energy* **2021**, *225*, 120240. https://doi.org/10.1016/j.energy.2021.120240
21. Pan, C.; Tan, J.; Feng, D. Prediction intervals estimation of solar generation based on gated recurrent unit and kernel density estimation. *Neurocomputing* **2021**, *453*, 552-562. https://doi.org/10.1016/j.neucom.2020.10.027
22. Jebli, I.; Belouadha, F.-Z.; Kabbaj, M.I.; Tilioua, A. Prediction of solar energy guided by pearson correlation using machine learning. *Energy* **2021**, *224*, 120109. https://doi.org/10.1016/j.energy.2021.120109
23. Liu, Y.; Li, L.; Zhou, S. Ensemble Forecasting Frame Based on Deep Learning and Multi-Objective Optimization for Planning Solar Energy Management: A Case Study. *Frontiers in Energy Research* **2021**, *9*, 764635. https://doi.org/10.3389/fenrg.2021.764635
24. Khan, W.; Walker, S.; Zeiler, W. Improved solar photovoltaic energy generation forecast using deep learning-based ensemble stacking approach. *Energy* **2022**, *240*, 122812. https://doi.org/10.1016/j.energy.2021.122812
25. Wang, L.; Mao, M.; Xie, J.; Liao, Z.; Zhang, H.; Li, H. Accurate solar PV power prediction interval method based on frequency-domain decomposition and LSTM model. *Energy* **2023**, *262*, 125592. https://doi.org/10.1016/j.energy.2022.125592
26. Al-Ali, E.M.; Hajji, Y.; Said, Y.; Hleili, M.; Alanzi, A.M.; Laatar, A.H.; Atri, M. Solar energy production forecasting based on a hybrid CNN-LSTM-transformer model. *Mathematics* **2023**, *11(3)*, 676. https://doi.org/10.3390/math11030676
27. Chaouachi, A.; Kamel, R.M.; Andoulsi, R.; Nagasaka, K. Multiobjective intelligent energy management for a microgrid. *IEEE transactions on Industrial Electronics* **2012**, *60*, 1688-1699.DOI: 10.1109/TIE.2012.2188873.
28. Fu, T.; Wang, C.; Cheng, N. Deep-learning-based joint optimization of renewable energy storage and routing in vehicular energy network. *IEEE Internet of Things Journal* **2020**, *7(7)*, 6229-6241. https://doi.org/10.1109/JIOT.2020.2966660
29. Zhang, G.; Hu, W.; Cao, D.; Liu, W.; Huang, R.; Huang, Q.; Chen, Z.; Blaabjerg, F. Data-driven optimal energy management for a wind-solar-diesel-battery-reverse osmosis hybrid energy system using a deep reinforcement learning approach. *Energy conversion and management* **2021**, *227*, 113608. https://doi.org/10.1016/j.enconman.2020.113608
30. Mohammed, N.A.; Al-Bazi, A. Management of renewable energy production and distribution planning using agent-based modelling. *Renewable energy* **2021**, *164*, 509-520. https://doi.org/10.1016/j.renene.2020.08.159
31. Yuan, H.; Tang, G.; Guo, D.; Wu, K.; Shao, X.; Yu, K.; Wei, W. Bess aided renewable energy supply using deep reinforcement learning for 5g and beyond. *IEEE Transactions on Green Communications and Networking* **2021**, *6(2)*, 669-684. https://doi.org/10.1109/TGCN.2021.3136363

32. Al-Janabi, S.; Mohammed, G. An intelligent returned energy model of cell and grid using a gain sharing knowledge enhanced long short-term memory neural network. *The Journal of Supercomputing* **2024**, *80(5)*, 5756-5814. https://doi.org/10.1007/s11227-023-05609-1
33. Kharrich, M.; Mohammed, O.H.; Alshammari, N.; Akherraz, M. Multi-objective optimization and the effect of the economic factors on the design of the microgrid hybrid system. *Sustainable Cities and Society* **2021**, *65*, 102646. https://doi.org/10.1016/j.scs.2020.102646
34. Oryani, B.; Koo, Y.; Rezania, S.; Shafiee, A. Barriers to renewable energy technologies penetration: Perspective in Iran. *Renewable Energy* **2021**, *174*, 971-983. https://doi.org/10.1016/j.renene.2021.04.052
35. Fares, D.; Fathi, M.; Mekhilef, S. Performance evaluation of metaheuristic techniques for optimal sizing of a stand-alone hybrid PV/wind/battery system. *Applied Energy* **2022**, *305*, 117823. https://doi.org/10.1016/j.apenergy.2021.117823
36. Yaïci, W.; Entchev, E.; Annuk, A.; Longo, M. Hybrid renewable energy systems with hydrogen and battery storage options for stand-alone residential building application in Canada. In *Proceedings of the 11th International Conference on Renewable Energy Research and Application (ICRERA)*, Istanbul, Turkey, **2022**, 317-323. https://doi.org/10.1109/ICRERA55966.2022.9922705
37. Izanloo, M.; Aslani, A.; Zahedi, R. Development of a Machine learning assessment method for renewable energy investment decision making. *Applied Energy* **2022**, *327*, 120096. https://doi.org/10.1016/j.apenergy.2022.120096