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Leveraging AI and Machine Learning Models for Enhanced Efficiency in Renewable Energy Systems

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Abstract. Artificial intelligence (AI) and machine learning (ML) have great potential in the management and optimization of renewable energy systems, through more in-depth AI-assisted analysis of store demand in the energy system, and through active learning models for energy optimization and scheduling. Among them, artificial intelligence and active learning can be combined to improve the utilization efficiency of renewable energy in a high range. In particular, recurrent neural network RNN and long- and short-term memory network LSTM in active learning can be used to predict energy and power demand, so as to achieve more effective intelligent power management and system optimization. Two of these models have their own advantages. LSTM and other active learning models can optimize the long-term dependence of traditional time series models and provide more efficient and accurate prediction model results for wind power forecasting and management and other renewable energy forecasting tasks. This study shows that compared with the traditional model, the LSTM model has a high advantage in processing long-term relationships and complex time series data, and the prediction results are more accurate and obvious. Through the dual combination of artificial intelligence and machine learning for renewable energy, this study provides theory, support and certain experimental guidance for the innovation of global energy systems, so as to make certain contributions to the development of renewable energy.

Keywords: Renewable Energy, Artificial Intelligence, Machine Learning, Power Demand Forecasting.

1. Introduction

The year 2023 marks an important turning point in the global energy sector. According to a report by global energy think tank Ember, renewable energy generation will account for 30% of global electricity for the first time in 2023, as a result of significant growth in solar and wind power. Solar in particular performed well, adding more than twice as much power as coal, making it the fastest-growing source of electricity for the 19th consecutive year. This change not only marks the possible peak of carbon emissions in the power sector but also signals the acceleration of the energy transition.

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Globally, and especially in China, the rapid expansion of wind and solar energy has had a profound impact on the global energy landscape. [1] China's contribution to global wind and solar power growth in 2023 will reach 60% and 51%, respectively. This achievement highlights the growing importance of clean energy technologies in the global energy system. However, while the increase in clean energy capacity was supposed to drive the decline in fossil fuels, the drought caused hydropower generation to decline, leading to a rise in coal generation, thereby increasing global power sector emissions by 1%.

As global electricity demand continues to grow, reaching a record high in 2023, the demand for clean energy is rising accordingly [2]. While energy demand has declined in some advanced economies, emerging markets, particularly China, Brazil and Africa, have shown rapid growth. This growth is placing higher demands on the energy system, requiring not only a massive push to expand clean energy, but also the introduction of advanced technologies to optimize the process of energy production and consumption.

Based on the above statement, AI and machine learning technology can be more efficient in terms of optimization and accurate prediction of renewable energy and model as well as production and article reading, and AI and active learning in daily life, more effectively manage and drive energy systems, and can make him more efficient sustainable development. In this study, a more comprehensive model, prediction and experimental analysis is carried out to improve the management and optimization of renewable energy systems by specifying the models of neural networks and long and short-term networks, and the excellent performance of RNNS and LSTMS in event sequence prediction provides critical support to the process of predicting the power energy system and production trend[3]. And through these learning model predictions, it is possible to optimize the production of renewable energy and achieve more intelligent and efficient management of in-store demand. By applying these advanced machine learning models, we expect to be able to predict electricity demand and production more accurately, enabling smarter and more efficient energy management and driving transformation and innovation in the global energy system.

2. Related Work

2.1. AI applications in renewable energy systems

Renewable energy is one of the key components of today's society, it is not only the core of the operation of industry, but also one of the key technologies that can promote the development and progress of science and technology, and renewable energy is a driving factor to maintain the convenience and convenience of our lives. However, due to the dual pressure of global warming and resource depletion, the sustainable development of traditional renewable energy has become one of the most concerned issues in the world, so the transformation of renewable energy has also become a global urgent task in the process of energy transformation, artificial intelligence technology, including its deep learning and other technologies, Through their superior data processing capabilities and intelligent decision-making capabilities, they can play a key role in promoting the renewable energy transition and the development of high-quality energy generation stars. [4]Based on these problems, this paper discusses the key role of artificial intelligence in the transformation process of renewable energy, analyzes how artificial intelligence improves energy efficiency and promotes the generation of star energy, and looks forward to the application of artificial intelligence in energy development, artificial intelligence in the traditional application of energy management and optimization. [5]It has significantly improved the efficiency of energy extraction and production, and at the same time promoted the development direction of more advanced and environmentally friendly industry. Among them, deep learning and data analysis, as well as active learning and other technologies can predict the storage location of energy under complex address conditions and optimize the extraction scheme to improve the production efficiency of energy [6]. In addition, artificial intelligence can also carry out real-time refining processes, that is, by intelligently adjusting parameters and improving efficiency to realize energy exploration in different fields and different environments.

Specifically, there are the following aspects: [7] First, in the energy exploration and production stage, artificial intelligence technology can accurately predict the distribution of resources by analyzing the current environmental and geological data and historical production record level, so as to optimize the drilling production plan and reduce the risk index and risk, and then optimize the energy production process while increasing the output. Moreover, the operation status of the equipment can be monitored, and the problems and risks of the equipment can be predicted in advance, so as to reduce the failure rate of the nuclear technology and equipment, optimize the energy production process, and ultimately improve the overall energy efficiency.In the energy production process, AI technology collects data through sensors on equipment, monitors equipment status in real time, and predicts potential failures for predictive maintenance[8-9]. This not only reduces unplanned downtime but also extends equipment life and increases productivity. Renewable energy contribution assessment and data-driven decision support

Renewable energy demand assessment and forecast The proportion of production and demand for different types of renewable energy, such as wind and solar, although the two are broadly the same, there is a big difference in the actual demand collection and analysis of production data for these energy types, so in the process of forecasting through the contribution to total energy, the process of forecasting[10], To model time series through modern machine learning techniques, predictive and regression analysis machine learning models can help these energy types, production trends and demand in different time periods and different patterns. These methods can accurately estimate the proportion of renewable energy demand, and can predict the future of energy, future trend prediction, etc., so as to provide data support for energy decision-makers.

Machine learning can also significantly optimize the configuration and management of renewable energy by optimizing data-driven decision-making capabilities[11]. Among them, the machine learning model can accurately and effectively control the real-time data of renewable energy, and the judgment of historical data and machine learning model, with energy allocation strategy, can optimize resource allocation to achieve demand prediction, thus providing strong support for policy making and investment decisions, and simulate different scenarios and policies on the basis of. Their potential impact on the development and economy of renewable energy can be assessed, helping policymakers and investors to make more informed investment decisions. This AI-driven data-driven analysis not only improves resource management and optimization, but also promotes the economic sustainability of renewable energy.

3. Methodology

3.1. Dataset

This dataset of this experiment and the analysis of the hourly training data of the store consumption and production, the data span five years, each entry contains a timeline and then the record and date and time node play a big role in the process. This data provides detailed information on consumption and production in the store. And several types of production data, including nuclear, wind, hydro, oil and gas, coal, solar and biomass.

The dataset enables comprehensive analysis of electricity trends and patterns, such as seasonal variations and the contributions of renewable energy sources. [12-13] It also supports investigations into fossil fuel dependence and can be utilized to enhance energy technologies and optimize production and consumption forecasting

Table 1. ElectricityConsumptionAndProduction

	DateTime	**Consumption**	**Production**	**Nuclear**	**Wind**	**Hydroelectric**	**Oil and Gas**	**Coal**	**Solar**	**Biomass**
0	2019/1/1 0:00	6352	6527	1395	79	1383	1896	1744	0	30
1	2019/1/1 1:00	6116	5701	1393	96	1112	1429	1641	0	30

Table 1. (continued).

2	2019/1/1 2:00	5873	5676	1393	142	1030	1465	1616	0	30
3	2019/1/1 3:00	5682	5603	1397	191	972	1455	1558	0	30
4	2019/1/1 4:00	5557	5454	1393	159	960	1454	1458	0	30

4. Key technologies and methods

4.1. Prediction model-RNN model

The electricity consumption forecast model around RNN consists of two shelves of 50 batteries. The first level returns the series, and the next level completes the output forecast. The model was compiled with the Adam optimizer and the dillomb function. The training (matsch) takes place over 20 periods, 80% of which is training data and 20% certification data. Loss of function indicates continuous improvement throughout the training cycle, indicating that learning is effective.

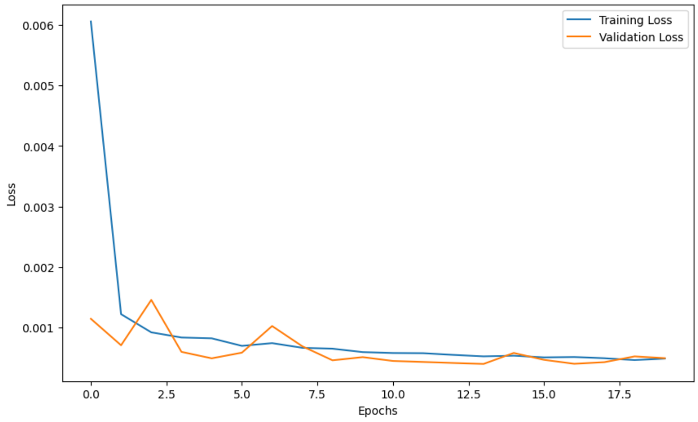

Figure 1. Simple RNN Training and Validation Loss

4.2. Model architecture and training process

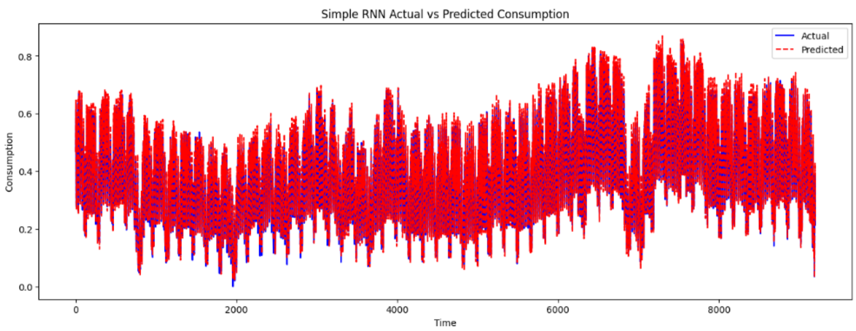

Figure 2. Simple RNN Actual vs Predicted Consumption

4.3. Predictive effectiveness and performance evaluation

The RNN model demonstrates strong predictive performance with an R^2 score of approximately 0.978, indicating that it explains about 97.8% of the variance in electricity consumption. The Mean Absolute Error (MAE) of 0.018 suggests minimal average deviation between actual and predicted values, while the Mean Squared Error (MSE) of 0.000576 and Root Mean Squared Error (RMSE) of 0.024 further

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underscore the model's accuracy and reliability in making predictions. The plots of actual versus predicted consumption illustrate the model's effectiveness in capturing the consumption trends.

Model architecture and training process: The LSTM model demonstrates a high level of predictive accuracy in forecasting electricity consumption. The evaluation metrics reveal an impressive R^2 score of 0.984, indicating that the model explains approximately 98.4% of the variance in the test data. The Mean Absolute Error (MAE) is 0.0156, which signifies minimal deviation between the predicted and actual values. The Mean Squared Error (MSE) stands at 0.00042, while the Root Mean Squared Error (RMSE) is 0.0205, both reflecting a high degree of model precision[14]. These metrics confirm that the LSTM model effectively captures the underlying patterns in electricity consumption data.

Specifically, if we use the LSTM model to predict the electricity production of a particular wind farm, we find that it more accurately predicts the amount of wind energy generated in the coming days because it is able to remember long-term trends in past wind speeds. In contrast, RNN models can also provide predictions, but they are less accurate. This suggests that LSTM has a stronger advantage in dealing with complex patterns and long-term trends in power data.

5. Conclusions

It can be seen from the overall review of articles and the experimental process that artificial intelligence has great prospects in the management and fear of renewable energy. For example, artificial intelligence can help optimize the use of wind energy and solar energy, which are common in our lives, and in the practical application of wind farms, artificial intelligence can analyze and analyze. The historical speed of the wind and the real-time speed of the wind can ensure the stability and accuracy of the power supply, which can help grid operators better arrange the production of electricity. In addition, artificial intelligence can also analyze the energy production and demand under different environments and different coefficients and give the best energy use strategy. For example, in the case of full sunshine, artificial intelligence can output the energy situation taking solar energy as an example, which can not only improve energy efficiency, but also be more environmentally friendly and make a certain transition to the energy system. All in all, the use of AI technology in the renewable energy industry can reduce carbon emissions for a more reliable and efficient protection of the climate as well as the entire global energy situation.

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