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Peak load estimation of renewable energy generation based on imitator dynamic algorithm

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Abstract

In the field of renewable energy generation forecasting, it is crucial to accurately estimate the peak load. However, due to the complex nonlinear characteristics of the data, the traditional long short-term memory network performs poorly in processing these data. This study introduces the imitator dynamic algorithm, which is able to generate samples close to the real situation by learning the change pattern of the data. Extensive experimental tests show that with the number of iterations increasing to 200, the prediction accuracy of the model reaches 62.35%, which is significantly better than that of the long short-term memory network, although it is decreased compared with the initial iteration. The imitator dynamic algorithm accurately learns the unknown data distribution according to two metrics of probability density and cumulative distribution within 5% error, demonstrating good generalization ability and robustness. These research results are of great significance for predicting the actual generation capacity of renewable energy. It not only enables grid operators to accurately predict and schedule power generation, but also supports sustainable energy development by improving grid stability and promoting the use of renewable energy.

Keywords: Imitator dynamic algorithm, Renewable energy, Peak load of power generation, Demand forecasting, Machine learning model

Introduction

In the global energy consumption pattern, the proportion of renewable energy is increasing year by year, which has become a key factor driving economic development and technological progress. However, the issue of accurate prediction and effective utilization caused by its randomness and uncontrollability, especially during peak load periods, has become an urgent challenge to be solved (Ozogbuda and Iqbal 2022; Oladigbolu et al. 2020a). Accurately estimating peak load can assist power grid operators in optimizing power grid dispatch and operation management, improving economic efficiency and stability of the power grid (Oladigbolu et al. 2020b; Okonkwo et al. 2022). This study aims to address the above challenges and propose the application of the Imitator Dynamic Algorithm (IDA) for estimating the peak load of renewable energy generation. The IDA is a reinforcement learning-based method that can imitate and predict

peak loads of renewable energy generation by simulating various states and decisions during power grid operation (Odou et al. 2020; Çelik et al. 2022). The innovation lies in the first application of the IDA to estimate the peak load of renewable energy generation, opening a new research path, and for the first time introducing Inverse Reinforcement Learning (IRL) into practical problems of power grid operation, achieving a combination of theory and practice. Other existing studies have also demonstrated various innovative methods used to address related issues. Specifically, Su C et al. developed an accurate optimization model that effectively determined the hourly power generation plan of cascade hydropower stations. Their results indicate that the model can optimize the short-term power generation plan of cascade hydropower stations under different hydrological conditions, whether it is during dry or flood seasons, and generate considerable total profits (Su et al. 2020). In addition, Rao G S et al. conducted a comparative study on the performance of various energy storage devices in multi regional power grids, selected a PID controller as the secondary control, and used the differential evolution artificial electric field algorithm to optimize the gain, highlighting the significant impact of energy storage devices in joint frequency and voltage control (Rao 2020). In addition, the spatiotemporal semantics and interaction graph aggregation method proposed by Fang Y et al. for multi-agent perception and trajectory prediction, which perceives and predicts traffic environments within a unified framework, has been validated to be superior to state-of-the-art methods (Fang et al. 2022). The research results will increase the efficiency and stability of power grid operation, reduce operating costs, and have significant economic value. At the same time, the research results provide new ideas and tools for researchers in related fields, promoting the in-depth development of theoretical research and practical applications, and has important social significance for promoting the widespread use of renewable energy and the sustainable development of power systems. The research will be conducted in four parts. The first part is an overview of the peak load of renewable energy generation based on the IDA. The second part is a model for studying the peak load of renewable energy generation based on the IDA. The third part is an experimental verification of the second part. The fourth part is a summary of the research content and points out the shortcomings.

Related works

The application of renewable energy is gradually increasing globally, and accurately estimating the peak load of these energy sources is of huge significance for the stable operation and optimized configuration of energy systems. Wang and other scholars have established a model for optimizing the short-term power generation plan of cascade hydropower stations in regional power grids, with the goal of minimizing the peak valley load difference among multiple power grids. This model not only considered traditional hydraulic constraints, but also considered the operational constraints, power constraints, and head effects of a single hydraulic unit. It was transformed into a mixed integer linear programming through a linearization strategy. The outcomes showed that the model was efficient and could effectively reduce the peak valley difference between the Shanghai and Zhejiang power grids, surpassing the actual operating performance (Wang et al. 2022). Li et al. proposed a new coordinated operation strategy for optimizing the combination of hydropower, thermal power, and wind

turbines, and applied this operation strategy to an improved IEEE 118 node power system. This optimization ensured the highest utilization rate of wind energy while addressing recent wind prediction errors. The presented results demonstrated the ability of the proposed strategy to configure operations based on multi-source energy systems (Li et al. 2022). Bedadi and Gebremichael designed and optimized a hybrid power system consisting of solar energy, micro hydropower, battery packs, and converters to meet the estimated total load based on residential needs. Simulation and optimization were based on factors such as load demand, climate data, and the economy of system components, aiming to minimize the total net present value cost. The results denoted that the optimized net present value and energy cost of the system were 78,763.26 US dollars and 0.0757 US dollars/kWh, respectively. The HOMER Pro simulation software tool effectively improved the design optimization effect of off grid and energy management systems (Bedadi and Gebremichael 2021). Munisamy and Sundarajan proposed a hybrid method called MASAAI, which combined mosquito search algorithm and artificial intelligence technology to achieve load frequency control of energy storage systems in multi region hybrid power systems and renewable energy. By integrating renewable energy sources such as solar energy, biomass energy, and fuel cells into the 3-zone system, system stability and power modulation control have been achieved. The simulation results in MATLAB/Simulink environment indicated that the MASAAI method was superior in efficiency to existing methods (Munisamy and Sundarajan 2021). Pavankumar et al. proposed the optimal grid connection based on photovoltaic, wind energy, biomass energy, and batteries to minimize annual lifecycle costs and the probability of power supply loss. When using MOACS to solve the optimal HRES design problem, probabilistic methods were used to consider the time-varying properties of RES and load. The results indicated that MOACS could provide better HRES optimization design (Pavankumar et al. 2021).

In this context, load estimation technology based on IDAs has attracted widespread attention as it can address the uncertainty and intermittency of renewable energy sources such as wind and solar energy. Balmik et al. proposed a IDA recognition framework that improved the robot's full body motion control ability in both single support and dual support stages, and achieved a 95% accuracy rate for human motion recognition. The experimental results expressed that the teleoperation framework had good robustness, providing strong support for the development and application of teleoperation robots (Balmik et al. 2022). Sharath's research team has proposed a map matching algorithm based on dynamic two-dimensional weights, which combined dynamic weight coefficients and road width to achieve lane level localization. The validation results showed that the algorithm performed excellently in identifying correct links and lane recognition accuracy, reaching 96.1% and 84% (Nottingham data) and 98.4% and 79% (Mumbai Pune data), respectively. The research results indicated that this algorithm could provide effective support for the application of intelligent transportation systems (Sharath and Velaga 2019). Maghami and Hosseini proposed a new deep reinforcement learning (DRL)-based analysis method for the band structure of thermoelastic wave propagation to optimize the design of layered phononic crystal (PC) beams. By defining the game of DRL agents, a DRL agent named Deep Deterministic Strategy Gradient (DDPG) was trained to achieve the expected band structure. The experimental results denoted that

this method could effectively automate the design of PCs, greatly improving design efficiency (Maghami and Hosseini 2022).

In summary, current research has some limitations in peak load estimation, especially in the field of renewable energy generation, and traditional methods are difficult to accurately cope with its instability and unpredictability. This study proposes to apply the imitator dynamic algorithm, which aims to improve the estimation accuracy by more accurately simulating the characteristics of renewable energy output. It is expected that the algorithm can predict the peak load more accurately, so as to provide stronger support for energy supply management and grid reliability, and provide a new perspective and methodology for subsequent research.

In the field of renewable energy generation forecasting, it is crucial to accurately estimate the peak load. However, due to the complex nonlinear characteristics of the data, the traditional long short-term memory network performs poorly in processing these data. This study introduces the imitator dynamic algorithm, which is able to generate samples close to the real situation by learning the change pattern of the data. Extensive experimental tests show that with the number of iterations increasing to 200, the prediction accuracy of the model reaches 62.35%, which is significantly better than that of the long short-term memory network, although it is decreased compared with the initial iteration. The imitator dynamic algorithm accurately learns the unknown data distribution according to two metrics of probability density and cumulative distribution within 5% error, demonstrating good generalization ability and robustness. These research results are of great significance for predicting the actual generation capacity of renewable energy. It not only helps grid operators accurately predict and dispatch power generation, but also supports sustainable energy discovery by improving grid stability and promoting the utilization of renewable energy. Studies such as Wang et al. (2022) and Li et al. (2022) have made progress in optimizing power systems and peak load estimation of renewable energy. However, these researches are usually limited in dealing with specific environments or small-scale systems, and have not effectively integrated multiple energy sources and realized dynamic prediction and scheduling in large-scale systems. Given these limitations, this study introduces the Imitator Dynamic Algorithm (IDA) to address the prediction and management challenges in complex energy systems. IDA has demonstrated excellent data adaptability and robustness in many fields, such as the research results of Balmik A and Sharath MN. We expect that IDA will show strong potential in accurately forecasting and managing peak loads of renewable power generation with significant uncertainty and intermittency, supporting the development of smart grids. The goal of the research is to improve the computational efficiency of IDA, expand its applicability to more complex power systems around the world, promote the efficiency of renewable energy, and contribute to the sustainable development of the power grid.

Building a peak load estimation model for renewable energy generation based on IDA

The study proposed a peak load estimation model combining IDA and IRL specifically for renewable energy generation. IDA uses the self-learning ability of environmental reward to adapt to uncertain energy data, while IRL optimizes the model by imitating the behavior of

historical data without complex reward mechanism. The model integrates VAE and GAN technology to generate high-quality data samples and improve the training effect under sparse data conditions. This approach has shown strong potential to deal with the peak load estimation problem of renewable energy generation both in theory and practice.

Requirement fitting of IRL algorithm and IDA based on behavioral cloning

In the estimation of peak load for renewable energy generation, it is necessary to predict and manage electricity demand and supply to ensure stable operation of the power system. It involves complex decisions and strategies, how to operate power generation equipment, and adjusting power generation strategies based on weather and electricity prices. The driving mechanism and laws behind this are complex and difficult to obtain directly from the data (Cheng et al. 2021; Liao et al. 2021). Therefore, advanced machine learning methods such as behavior cloning-based IRL algorithms and IDAs are needed to learn from expert behavior to make better decisions in response to new unknown situations. These methods enable research to better understand and predict electricity demand and supply, develop better generation strategies, improve power system operational efficiency, reduce costs, and enhance stability and reliability. By utilizing the IRL algorithm of behavior cloning and the IDA, it is possible to learn from expert behavior to optimize decision-making, understand and predict power demand and supply, thereby improving the efficiency and stability of power system operation. This is actually a form of "supervised learning". The schematic diagram of supervised learning is denoted in Fig. 1.

In Fig. 1, behavior cloning corrects errors in expert examples by learning them and forming a new training dataset. Reverse reinforcement learning faces the problem of multiple reward functions that can explain expert behavior, while maximum entropy reverse reinforcement learning solves this problem by using the maximum entropy model to avoid bias and obtain unknown reward functions. The definition of information entropy is shown in Eq. (1).

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log (p(x_i)) \tag{1}$$

In Eq. (1), $H(X)$ is the information entropy, and $p(x_i)$ is the initial state of the example. In the estimation of peak load for renewable energy generation, the maximum

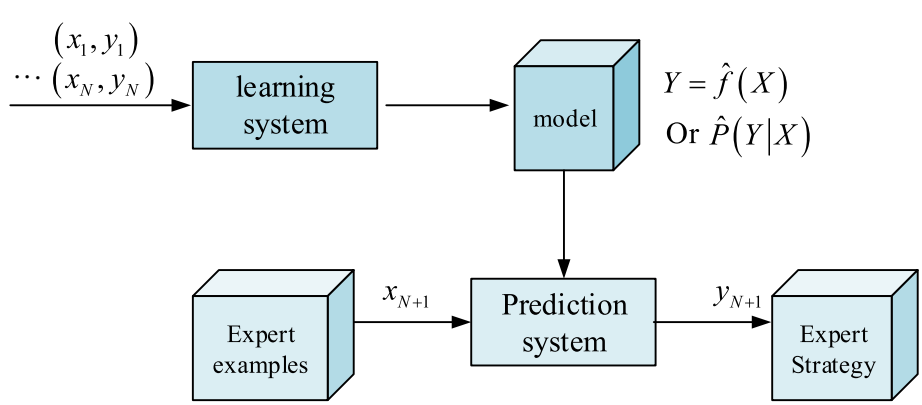

Fig. 1 Schematic diagram of supervised learning

entropy principle can be applied to optimize the decision-making process. Due to the randomness of the environment, there may be many samples that meet feature expectations, so the study uses maximum entropy distribution to describe the distribution of sample trajectories. This method can handle the uncertainty and noise observed in the examples, thereby obtaining a more accurate reward function. The maximum entropy IRL algorithm utilizes the maximum entropy principle to avoid any bias and obtain unknown reward functions. The path expression with a higher total reward for the maximum entropy value is shown in Eq. (2).

$$P(\zeta|\alpha) = \frac{1}{Z(\alpha)} \exp\left(R(\zeta|\alpha)\right) \tag{2}$$

In Eq. (2), α is the weight of the reward function, is the partition function obtained by summing all paths, and is the probability reward and total reward of the paths under the weight, respectively. It aims to obtain the optimal parameters for an action α, as shown in Eq. (3).

$$\alpha^* \propto \arg\max_{\alpha} L_\alpha = \arg\max_{\alpha} \sum\nolimits_{i=1}^{n} \log P(\zeta|\alpha) \tag{3}$$

In Eq. (3), L_α is the linear partial derivative weight value. This process is essentially a learning process, through which an optimal action strategy can be obtained. The learning process of this strategy can be seen as a cloning behavior, as it attempts to replicate the optimal action. Therefore, the process of reverse reinforcement learning algorithm based on behavior cloning is to analyze the optimal behavior strategy to obtain the best learning results. The process of reverse reinforcement learning algorithm based on behavior cloning is shown in Fig. 2.

In Fig. 2, the IRL algorithm first utilizes behavioral cloning technology to generate new near optimal expert examples, and then uses the maximum entropy IRL method to obtain the reward function. IDAs are used to achieve dynamic matching of peak loads for renewable energy generation. The IDA of the renewable energy generation peak load is shown in Eq. (4).

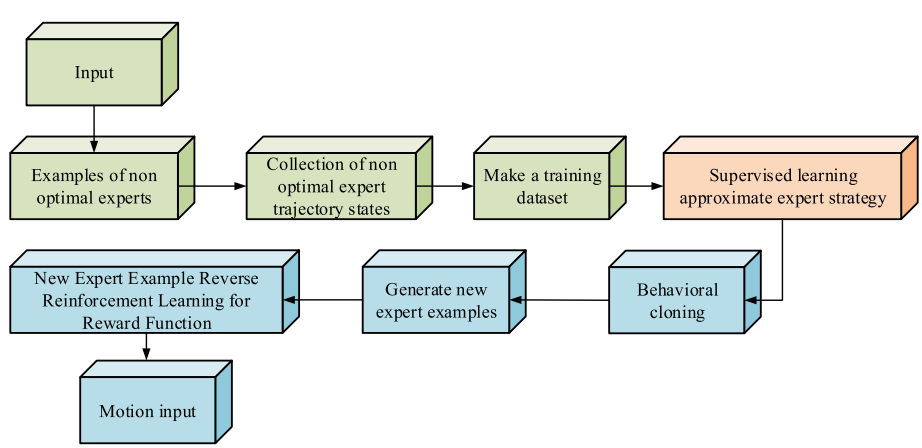

Fig. 2 Process of IRL algorithm based on behavior cloning

$$\frac{dG}{dt} = f(G) = [B(n_i, N), B(s_i, S), B(u_i, U)] \tag{4}$$

In Eq. (4), $f(G)$ is the dynamic equation of the application virtual resource emulator; B is the expected fitting function; n_i is the target participating resources in the random matching game stage; s_i is the execution space in the random matching game stage; s_i is the resource return in the random matching game stage. The calculation for the success rate of task execution is shown in Eq. (5).

$$P = \frac{c}{C} \times 100\% \tag{5}$$

In Eq. (5), P is the success rate of matching task execution; P is the number of successful resource matching scheduling executions; P is the degree of resource matching execution, with high matching accuracy and task success rate. The resource utilization rate is shown in Eq. (6).

$$W = \frac{e}{E} \times 100\% \tag{6}$$

In Eq. (6), W is the resource utilization rate; e is the total amount of utilized resources; E is the total amount of available resources in game matching (Atanassov 2022). The corresponding probability formula is shown in Eq. (7).

$$\eta = \frac{q_{ij} f(G)}{\sum Qf(G)} \tag{7}$$

In Eq. (7), η is the probability of being selected during the game matching process of resource individuals; q_{ij} is the demand strategy after j iterations at i time, and j is the demand strategy distribution system. After calculating the peak load resources of renewable energy generation that meet the demand one by one, the result with the highest probability is used as the matching result. When a structure that reaches the probability value occurs during the calculation process, the calculation is ended and used as the matching target. By doing so, the dynamic matching of peak loads and resources for renewable energy generation can be achieved.

Generation of peak load estimation for renewable energy generation based on VAE/GAN

After conducting in-depth research on the demand fitting of behavior cloning-based IRL algorithms and IDAs, this chapter will further explore how to use VAE and GAN to generate peak load estimation for renewable energy generation. The combination of these two methods is expected to further improve the accuracy and stability of prediction, optimize the operational efficiency of the power system, and offer effective tools for achieving the maximum utilization of renewable energy. The study will explore how to optimize the estimation of peak load for renewable energy generation using VAE and GAN. This encoding technique creates alternative data as input features, which can improve the training effectiveness of renewable energy peak load estimation and compensate for expert example errors. With the help of Auto Encoder (AE), IRL, and IDAs, power demand and supply can be more accurately predicted, generation strategies can be optimized, power system efficiency can be improved, costs can be reduced, and

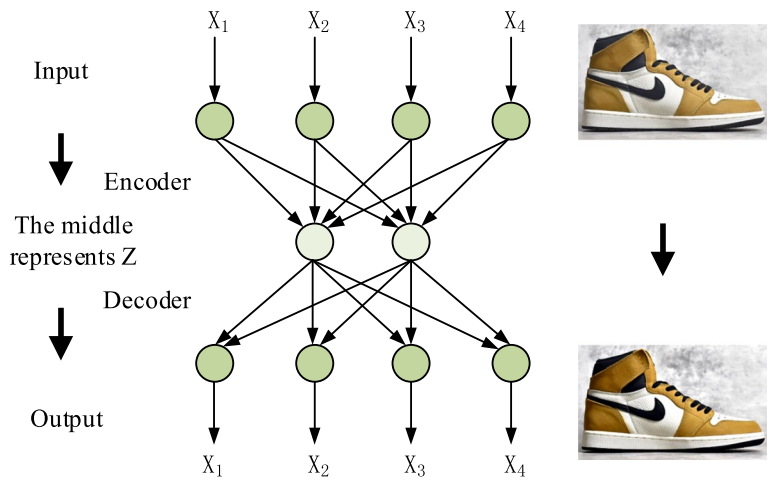

Fig. 3 Network structure of AE

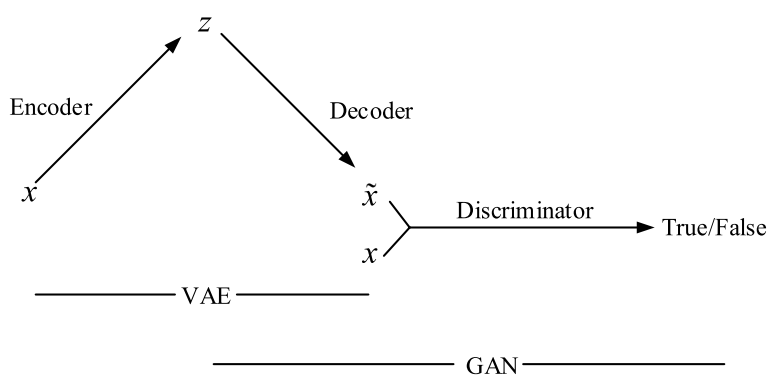

Fig. 4 The Combination model of VAE and GAN

stability and reliability can be enhanced. AE is an unsupervised learning method in the field of machine learning, which can learn the high-dimensional distribution of input sample sets and perform low-dimensional feature encoding. Due to the ability of automatic encoders to achieve low dimensional encoding of high-dimensional data, they can be used to construct new alternative data as feature representations for input data. The network structure of AE is shown in Fig. 3.

In Fig. 3, the encoder and decoder form an AE for encoding and decoding input samples to achieve sample reconstruction. The encoder simplifies complex input samples, and the decoder generates outputs that are similar to the original samples. By limiting the intermediate encoding dimension, data compression and feature extraction can be achieved, generating samples that are similar but not completely identical to the original sample. The combination model of VAE and GAN is shown in Fig. 4.

In Fig. 4, the VAE/GAN model combines the strong generative power of generating adversarial networks with the feature representation ability of VAE. During the training process, the model completes encoding, reconstruction, and discrimination of the samples. The model with improved structure can more effectively utilize potential features for sample similarity measurement. VAE can refer to the feature representation of discriminative data and use feature level error to measure data distribution patterns.

By utilizing more meaningful similarity measures for the reconstruction objectives, the VAE/GAN model can generate higher quality samples. The reconstruction and restoration expression of the output sample is shown in Eq. (8).

$$\begin{cases} z \sim Enc(x) = q(z|x) \\ \tilde{x} \sim Dec(z) = p(x|z) \end{cases} \tag{8}$$

In Eq. (8), x is the encoding of the output sample and z is the reconstructed input sample. Due to the insufficient element level reconstruction error for images and other signals with invariance, a Gaussian observation model is used, as shown in Eq. (9).

$$p(Dis_i(x)|z) = N\left(Dis_i(x)\middle|Dis_i\left(\tilde{x}\right), I\right) \tag{9}$$

In Eq. (9), $Dis_i(x)$ is the output representation of the $Dis_i(x)$ th layer of the discriminator network, and $\tilde{x} = Dec(z)$ is the decoding sample of x. The reconstructed combined model is shown in Eq. (10).

$$L = L_{prior} + L_{Ilike}^{Dis_l} + L_{GAN} \tag{10}$$

In Eq. (10), both *Dec* and *GAN* are mapped from the input variable z to the output space x, and while their functions are the same, *GEN* can be replaced by *Dec*. The training process of VAE/GAN is shown in Fig. 5.

In Fig. 5, the encoder and discriminator use a convolutional network to output sample the input samples through three convolutional layers. The decoder structure is the opposite, including three deconvolution layers. The hidden layers of encoders, decoders, and discriminators all use ReLU activation functions. Considering the stable role of batch standardization in traditional GAN models, batch standardization has also been adopted in encoders, decoders, and discriminators. To generate real renewable energy scenarios, the VAE/GAN model is applied to model the unknown distribution data of renewable energy, which is difficult to accurately characterize the randomness, volatility, and intermittency of wind and solar power. Both the encoder and discriminant network use random gradient descent to update parameters for training. The encoder achieves mapping from a prior distribution to the generated data space by minimizing reconstruction

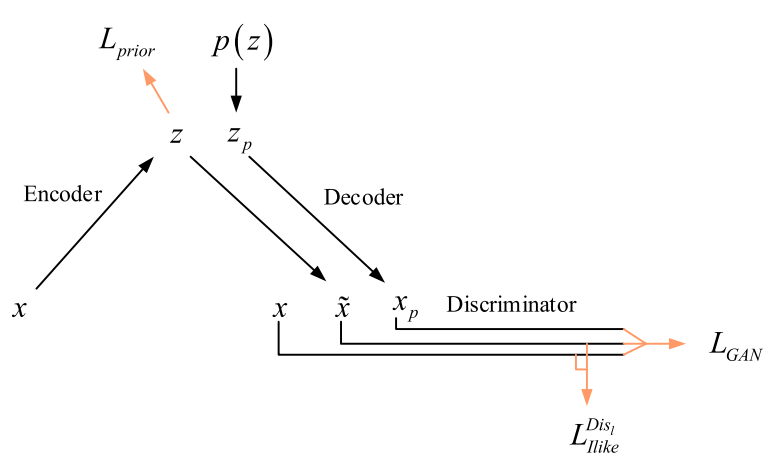

Fig. 5 The training process of VAE/GAN

errors, while the discriminative network is trained to distinguish between real samples and generated samples. Decoder parameter weighting is shown in Eq. (11).

$$\theta_{Dec} \overset{+}{\leftarrow} \nabla_{\theta_{Dec}} \left(\gamma L_{Ilike}^{Dis_i} - L_{GAN} \right) \tag{11}$$

In Eq. (11), γ is the parameter and $L_{Ilike}^{Dis_i}$ is the signal error. The Gaussian radial basis kernel function between matrices is shown in Eq. (12).

$$K(x, y) = \exp\left(-\|x - y\|^2 / \left(2\sigma^2\right) \right) \tag{12}$$

In Eq. (12), GAN is the kernel function bandwidth, and then the time is estimated as shown in Eq. (13).

$$\hat{t} = \frac{MMD}{\sqrt{\hat{v}}} \tag{13}$$

In Eq. (13), v is the asymptotic equation for v estimation.

Building a renewable energy generation peak load estimation model based on optimized IDA

The introduction of optimized IDAs has played a crucial role in the construction of peak load estimation models for renewable energy generation. Firstly, behavioral cloning technology is used to learn from the operational strategies of experts to obtain preliminary dynamic models. Then, through an automatic encoder, the complex dynamic system is dimensionally reduced to more effectively understand and predict its behavior. Subsequently, the optimized IDA Is used to further optimize the model, improving its prediction accuracy by adjusting parameters such as learning rate and iteration times. Finally, the optimized model will be applied to actual power generation systems to predict peak load demand and achieve more effective energy allocation and management. The process of building a peak load estimation model for renewable energy generation is shown in Fig. 6.

In Fig. 6, when establishing a renewable energy peak load prediction model based on the IDA, historical load data, including power generation and related environmental factors, is first collected. These data are input into the algorithm for training and generate imitation strategies. During the training process, it may be necessary to

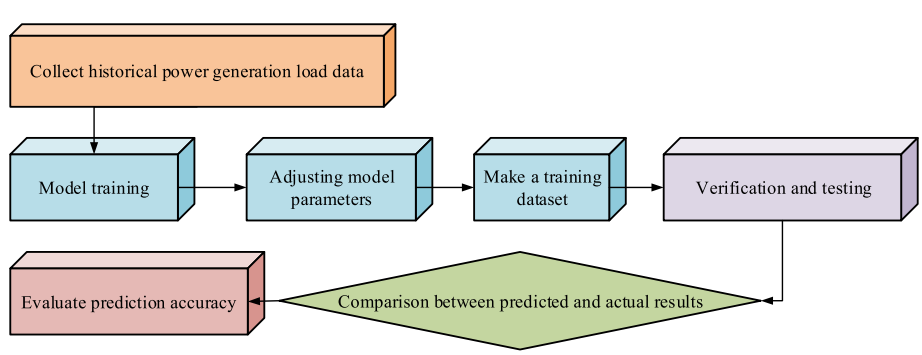

Fig. 6 Construction process of peak load estimation model for renewable energy generation

adjust parameters to narrow the gap between predicted and actual results. Finally, the accuracy of the model is evaluated and tested by comparing the predicted and actual outcomes. In the peak load estimation system for renewable energy generation, the detection object signal of any peak load is denoted in Eq. (14).

$$Y_j = \sum_{i=1}^{m} \left|X_{ij}\right|^2 \tag{14}$$

In Eq. (14), X_{ij} is the j th sampling value in the i th peak load received signal. i is the sampling point amount, and m refers to the received signal's sum of sampling points. Based on the limit theorem, the received signal energy's the Gaussian distribution is expressed in Eq. (15).

$$Y \sim \begin{cases} N(m, 2m), & H_0 \\ N(2m(\lambda+1), 2m(2\lambda+1)), & H_1 \end{cases} \tag{15}$$

In Eq. (15), λ means the instantaneous signal-to-noise ratio at any peak load; $N(m, 2m)$ denotes the Gaussian distribution of mean m and variance m. At H_1, $N(2m(\lambda+1), 2m(2\lambda+1))$ represents the Gaussian distribution of mean m and variance $2m(2\lambda+1)$. The fusion center compares the fuzzy integral values of two types of fuzzy integrators based on a predetermined decision strategy, and makes the final decision, as shown in Eq. (16).

$$sum_1 = \sum_{i=1}^{n} a_{total1j} \tag{16}$$

In Eq. (16), $a_{total1j}$ indicates the fuzzy integral value of the j th peak load on the H_0 fuzzy integrator, and n expresses the amount of peak loads in the entire system. The sum of fuzzy integral values is shown in Eq. (17).

$$sum_0 = \sum_{i=1}^{n} a_{total0j} \tag{17}$$

In Eq. (17), $a_{total0j}$ refers to the fuzzy integral value of the j th peak load on the H_0 fuzzy integrator, and the fusion center compares the value of the sum of the two fuzzy integrals of the H_0 and H_1. Based on the sum of the fuzzy integral values corresponding to the fuzzy integrator, the main user signal's state is determined. When sum_0 is greater than sum_1, the main load signal is determined not to exist. Conversely, the main load signal exists.

Analysis of peak load estimation for renewable energy generation based on IDA

The purpose of this study was to use IDAs to predict the peak load of renewable energy generation. Firstly, the characteristics of this algorithm was utilized for model training and optimization. Then, the accuracy, practicality, and stability of the predicted results were evaluated to verify the effectiveness of the model.

Effectiveness analysis of the model optimized by IDA

After building a renewable energy generation peak load estimation model based on the IDA, the optimization effect will be further analyzed. The effectiveness of model optimization depends on multiple factors, among which precise adjustment of algorithm parameters and suitable hardware and software support are crucial. For the adjustment of algorithm parameters, it is necessary to optimize based on the actual situation, taking into account factors such as model accuracy and stability. Five wind power plants and five solar power plants were selected for the experimental scenario. These power plants are located in different climate zones, deployed in diverse geographical environments from coastal to inland, and from plateaus to plains, providing continuous hourly power generation and environmental data for two years. The selection of hardware and software should consider both performance and cost to achieve the best operational results. The relevant hardware and software parameters are shown in Table 1.

The core purpose of this experiment is to evaluate the accuracy of IDA in predicting peak loads of renewable energy generation, as well as the stability and universality of the model. The study compared the effectiveness of intelligent fault diagnosis networks optimized based on IDAs with those based on long and short-term memory (LSTM) networks. Firstly, it conducted experiments using the original dataset. Compare the IDA optimized intelligent fault diagnosis network with the LSTM based network, and record the average fault diagnosis accuracy of the two methods after 100, 150, and 200 iterations. The data is shown in Fig. 7.

In Fig. 7, compared to the LSTM network, the proposed algorithm performed better, with an average accuracy significantly higher than the LSTM network. The accuracy of both algorithms started from zero. However, as the amount of iterations increased, the accuracy of the proposed algorithm quickly rose to a high level of 70.25, significantly

Table 1 Related hardware and software parameters

Category	Parameter/specification	Description	Value/details
Algorithm parameter	Alpha	Learning Rate in the imitation dynamics algorithm	0.01
	Num_epochs	Number of training epochs	100
	Batch_size	Size of the mini-batch for stochastic gradient descent	32
	Gamma	Discount factor in the reward function	0.99
	Epsilon	Epsilon value for the epsilon-greedy exploration strategy	0.1
	Lambda	Regularization parameter for the reward function	0.001
Hardware specification	CPU	Central processing unit	Intel® Core™ i7-8700 K CPU @ 3.70ghz
	RAM	Random access memory	32 GB
	GPU	Graphics processing unit	NVIDIA geforce GTX 1080 Ti
Software specification	Operating system	The software platform	Ubuntu 18.04 LTS
	Programming language	Coding language used	Python 3.7.10
	Libraries/Frameworks	Supporting software tools	Tensorflow 2.3.0, Numpy 1.19.5, Pandas 1.1.5, Matplotlib 3.3.4, Scikit-learn 0.24.1

surpassing the performance of LSTM networks under the same amount of iterations, highlighting the advantages of the proposed algorithm in fault diagnosis. However, when the amount of iterations increased to 200, the accuracy of the proposed algorithm decreased to 62.35. Despite some decline, the overall performance was still significantly better than that of LSTM networks. This phenomenon may be due to overfitting of the model as the number of iterations increased, leading to a decline in its performance on unknown data. The impact of data normalization on model accuracy is shown in Fig. 8.

In Fig. 8, data standardization can significantly improve the accuracy of model prediction, and almost all types of faults can be accurately detected, while non standardized data has poor results, with only partial faults being detected. Before conducting multi classification tasks, it is necessary to convert the original data labels into one hot encoding to make the calculation of distance between categories more reasonable. After using the IDA optimization, the predictive model of the power generation system has significantly improved. Especially when predicting peak load demand, the accuracy is greatly improved, which is crucial for better energy management.

Analysis of load estimation results based on IDA

A detailed case study is presented to show the application of load estimation results based on the simulator dynamic algorithm in real solar and wind power generation systems. Each case is derived from real power system operation data, thus allowing the study to validate the actual performance and accuracy of the algorithm. These data not only demonstrate the effectiveness of the algorithm in estimating load, but also support the research hypothesis that through model learning, research can improve the prediction accuracy of power system behavior. The load data utilized in this study are derived from actual solar and wind power generation systems in a certain area of China, from which the study has collected detailed hour-level capacity records over the past year. The dataset contains over 8760 records and has been quality checked and pre-processed to ensure accuracy and consistency. The preprocessing steps include missing values imputation, outlier removal, and data normalization, aiming to prepare reliable inputs

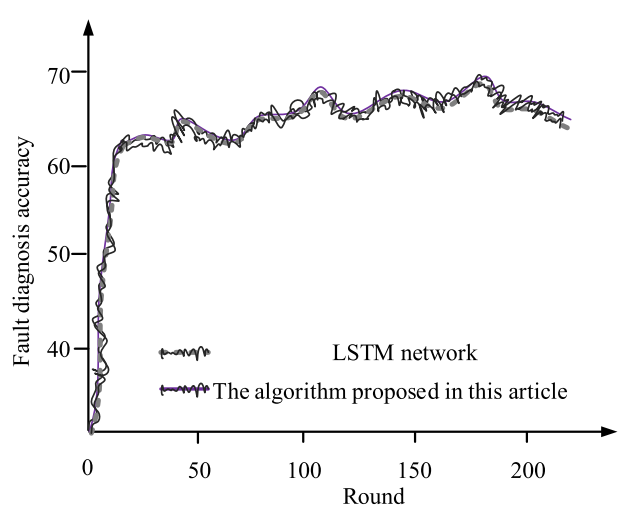

Fig. 7 Average fault diagnosis accuracy

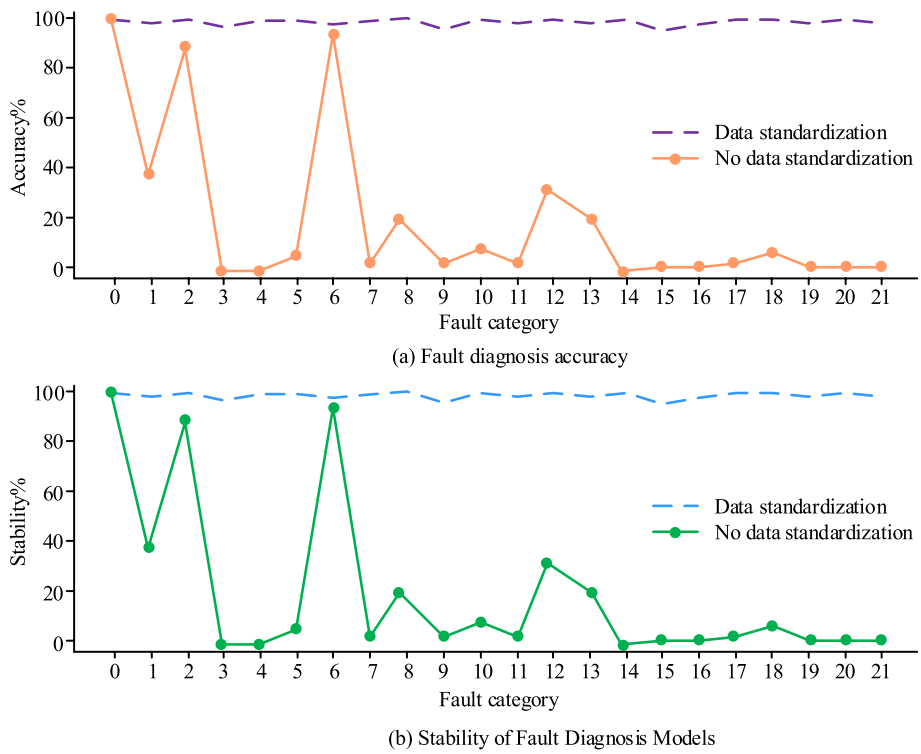

Fig. 8 The impact of data normalization on model accuracy

for algorithm training. In practical applications, the algorithm's estimated load results were consistent with the actual values, and the error range was small, effectively improving the operational efficiency of the power system. In addition, this algorithm had good adaptability to different types and scales of power systems, further improving its application value. The sample load estimation results during the solar energy data training process are shown in Fig. 9.

In Fig. 9, there was a significant difference between the reconstructed samples of the VAE/GAN model and the test samples during the initial training period (as shown in Fig. 9a and b). As the training progressed, the model gradually grasped the real data variation patterns, and the fluctuation characteristics of the generated samples gradually approached the real scene. In Fig. 9c and d, after 90 cycles of training, the fluctuation characteristics of the test samples and reconstructed samples were basically consistent, proving that the data generated by this method can effectively reflect the dynamic behavior of real wind power data. The data showed that the fluctuation range of the reconstructed sample was within 1%. The samples during the wind power data training process were consistent with the estimated results, as shown in Fig. 10.

In Fig. 10, the reconstructed samples effectively reflected the fluctuation and intermittent characteristics of wind and solar power generation. After model training, the generator could generate a large amount of data samples for statistical analysis. Based on the two indicators of probability density and cumulative distribution, the model accurately learned the unknown data distribution patterns within a 5% error range. Through the simulation analysis of solar and wind power generation load, the model shows an error

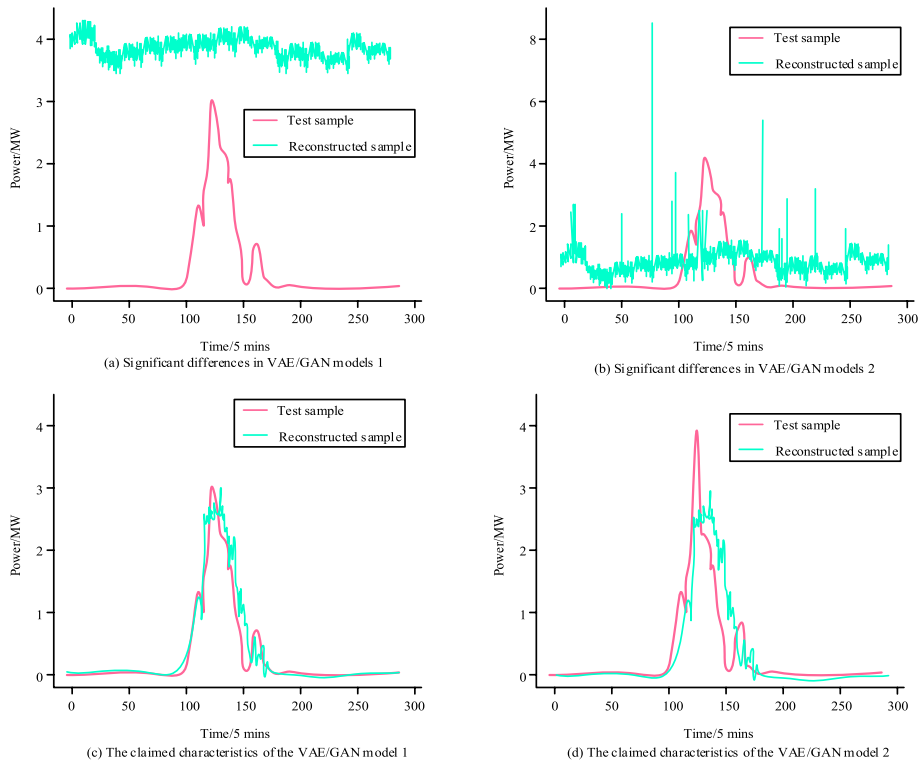

Fig. 9 Sample load estimation results during solar data training process

range within 1% in the estimation results, which is far better than the industry standard error tolerance value of 5%. Compared with traditional forecasting methods, such as moving average or linear regression analysis, the proposed algorithm shows more stable and accurate load tracking. Through statistical analysis, we further evaluate the probability density function and cumulative distribution function of the generated samples, which confirms the ability of the model to learn unknown data distribution.

The case study highlights the potential application of simulator based dynamic algorithms in the field of solar and wind load estimation. The experiment has proven that this algorithm not only improves the operational efficiency of the power system, but also provides a new perspective for decision support in related industries. The results of this study lay the foundation for further applying such models in other types of renewable energy, and future work will explore the applicability and optimization methods of algorithms in a wider range of scenarios.

The proposed load estimation method based on mimic dynamic algorithm is studied, and accurate load prediction is achieved in a simulated environment. The application of this technology in real power systems can provide critical load data for operators to help cope with power supply fluctuations and peak loads and ensure grid stability. In the field of renewable energy, the algorithm can optimize production strategies and enhance the flexibility of electricity market transactions. Integrated into the smart grid system, the algorithm will promote the accurate execution of grid scheduling and maintenance decisions. The algorithm has the potential to cross industry boundaries, and can be applied to other fields that need precise load forecasting, such as manufacturing and retail.

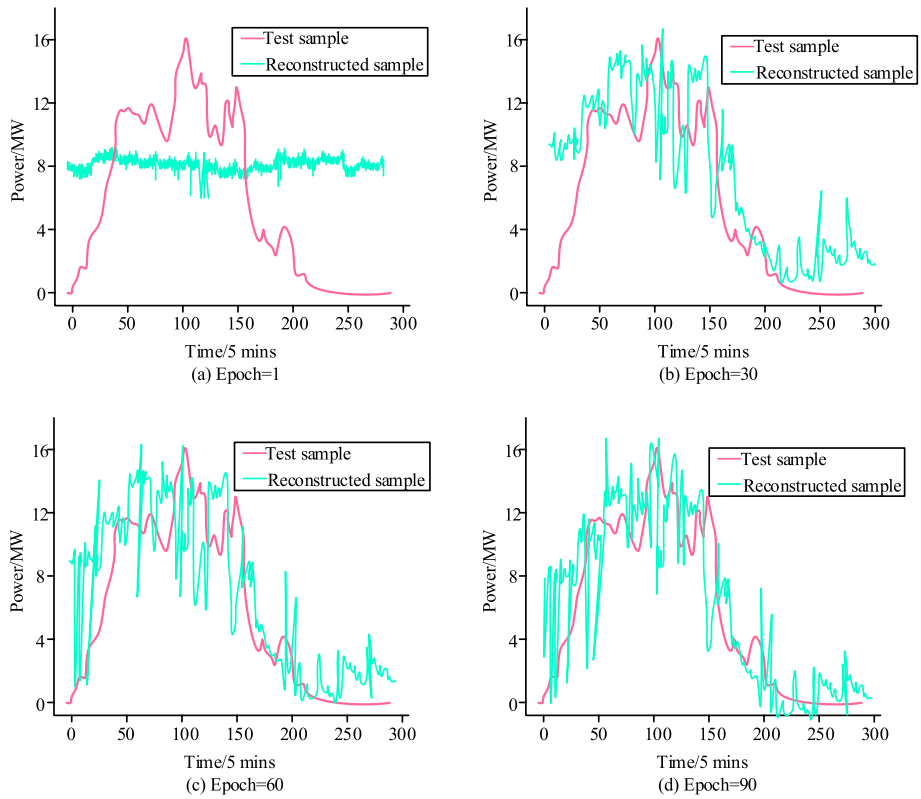

Fig. 10 The samples in the wind power data training process are consistent with the estimated results

Conclusion

In the prediction of renewable energy generation, peak load estimation is crucial, but traditional LSTM networks have poor performance in handling complex nonlinear data. To address this issue, the study introduced the IDA as a new prediction tool. This algorithm is based on real data and generates samples that are close to real scenes by replicating their change patterns. The results indicated that as the amount of iterations increased, the prediction accuracy of the algorithm quickly increased to 70.25%, significantly surpassing the performance of LSTM under the same amount of iterations, highlighting the advantages of the algorithm in fault diagnosis. In addition, by converting the original data labels into one hot encoding, the calculation of distance between categories was more reasonable, thereby improving the accuracy of multi classification tasks. After 90 cycles of training, the fluctuation characteristics of the test samples and the reconstructed samples were basically consistent, proving that the data generated by this method can effectively reflect the dynamic behavior of real wind power data, and the fluctuation range of the reconstructed samples was within 1%. Although in renewable energy generation forecasting, IDA shows the advantages of dealing with complex nonlinear data and significantly improves the accuracy when iteration increases, this forecasting tool may face challenges in extreme climate conditions. IDA is able to generate high accuracy predictions for standardized data and general patterns of fluctuations, but it is not guaranteed to be effective in extreme climate scenarios. The difficulties of data collection caused by extreme weather, the weakening of model adaptability and

the decrease of prediction reliability are the main limitations faced by IDA. In addition, IDA relies on existing data to learn and generate samples. If the existing data is not sufficient to cover all potential power generation patterns and environmental conditions, the generated samples may not fully reflect the actual complex diversity. Therefore, future research needs to expand the coping scope of IDA, including better learning of data change patterns under extreme weather, and exploring the possibility of introducing more diverse data sources to enhance the robustness and application breadth of the model in different scenarios.

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Author contributions
SY: contributed to the motivation, the interpretation of the methods, the data analysis and results, and provided the draft versions and revised versions, references. LY: provided the data and results, the revised versions and references. JL: provided the related concepts and minor recommendations, extracted the conclusion and discussion.

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Availability of data and materials
The data will be made available on request.

Declarations

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Not applicable.

Consent for publication
Not applicable.

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