



The Application of Machine Learning in Parameter Adaptive Control of Virtual Synchronous Generators

Shutian Yang

Electronic Information School Wuhan University, 430072, Wuhan, Hubei, China
2022302121332@whu.edu.cn

Abstract. Virtual Synchronous Generator (VSG) enhances system stability by simulating the inertia and damping characteristics of synchronous generators. However, due to the fixed parameters, it is prone to cause low-frequency oscillations. To address this issue, scholars at home and abroad have proposed stability analysis methods based on small-signal models and introduced recurrent neural networks (RNN) and other neural network technologies into VSG control to achieve online adaptive parameter adjustment. This paper reviews the application of machine learning methods in the adaptive control of VSG parameters. Firstly, the classification and principles of machine learning were introduced. Then, the applications of small-signal modeling methods, RNN and other neural network algorithms in the VSG system were respectively presented, and specific cases and comparative analyses were given. Finally, the main challenges and research trends currently faced are discussed to provide reference opinions for the further development of related fields. Therefore, in-depth research on the application of machine learning in the adaptive control of VSG is of great significance for enhancing the stability and operational efficiency of power systems with a high proportion of new energy.

Keywords: First Keyword, Second Keyword, Third Keyword.

1 Introduction

With the continuous increase in the proportion of renewable energy generation, the inertia and damping of the power system have significantly declined, and the frequency stability is facing severe challenges. The Virtual Synchronous Generator (VSG) technology provides "virtual inertia" and damping support for high-proportion new energy power grids by simulating the rotational inertia and damping characteristics of synchronous generators and has become an important means to maintain frequency stability [1]. However, traditional VSG usually adopts a fixed inertia coefficient J and a damping coefficient D , whose parameters are set to constant values during design. In actual operation, the load and the output of distributed power sources are constantly changing. The VSG with fixed parameters is difficult to balance the rapid response and steady-state error optimization in the dynamic process in a timely manner and is prone to cause

problems such as low-frequency oscillation or small interference instability under certain working conditions. This characteristic of being sensitive to fixed parameters makes it difficult for traditional VSG control to adapt to variable working conditions.

In recent years, researchers have begun to introduce machine learning methods into the field of VSG parameter optimization to enhance the robustness and adaptability of VSG control. Ghodsi et al. proposed a deep neural network controller that combines RBM with MLP to form a multi-layer network [2]. Lu Anyu et al. proposed a strategy of using the CNN-LSTM hybrid model to predict the system frequency and applying the prediction results to adaptively adjust the inertia and damping of VSG [3]. Lu et al. adopted the SAC algorithm (Soft Actor-Critic) for model-free optimization control and suppressed frequency and active power oscillations by adjusting the virtual inertia and damping of VSG in real time [4].

This article will focus on this theme and review the application research of machine learning in VSG parameter adaptive control in recent years. Firstly, it will introduce the specific applications and progress of methods such as supervised learning, deep learning, reinforcement learning, and multi-agent learning in VSG control. Then, analyze the typical algorithms and cases of various methods, and compare the control characteristics, advantages, limitations and applicable conditions of different methods. Finally, in light of the current challenges, we look forward to the future development direction.

2 Overview of machine learning technology

Machine learning can be classified into categories such as supervised learning, unsupervised learning, reinforcement learning, and deep learning based on training methods and application scenarios. In the field of VSG parameter adjustment, these methods each have their own characteristics:

Supervised Learning achieves parameter adaptive adjustment by training an input-to-output mapping model using historical data to predict the optimal system parameters or control quantities in a given state. Supervised learning methods have a fast-computing speed and can quickly provide parameter adjustment suggestions after disturbances occur. However, their performance depends on the quality and coverage of the training data, making it difficult to adapt to new working conditions outside the training data in a timely manner.

Deep Learning, in a broad sense, belongs to a subset of supervised learning. Its core lies in using deep neural networks (Deep Learning models) to achieve data learning and representation [5]. Deep learning models have stronger expressive capabilities, but they usually require a large amount of diverse data for training, and the network structure and hyperparameter tuning are also relatively complex.

Reinforcement Learning is a method that learns the optimal sequential decision-making strategy through the repeated interaction between the Agent and the environment. Reinforcement learning does not rely on explicit system models and is suitable for highly nonlinear and difficult-to-model scenarios. However, the training process of

the RL method is rather complex, usually requiring a large number of simulation interactions and repeated iterations to converge. Moreover, the design of the reward function directly affects the performance of the strategy and needs to be carefully designed in combination with control requirements.

Unsupervised Learning is a method of training by finding the distribution and feature patterns of the data itself, such as clustering, dimensionality reduction, principal component analysis, etc. In VSG control, unsupervised learning is mainly used for feature extraction and pattern recognition, and there are relatively few studies directly applying it to parameter adjustment. However, unsupervised techniques can serve as an aid, for instance, by extracting feature components from historical operational data and then combining them with other algorithms for control.

Supervised learning and deep learning place more emphasis on training mapping models using offline data, which are suitable for quickly estimating parameters or system responses within a known range of operating conditions. Reinforcement learning emphasizes online interactive trial and error and is expected to adaptively adjust strategies in unknown or changing environments. Unsupervised learning has limited applications in this field.

3 Application of Machine Learning Methods in VSG Parameter Adaptive Control

3.1 Supervised learning methods

Supervised learning methods have been applied in the research of VSG parameter optimization for a long time due to their relatively simple implementation principle and fast inference speed. A typical approach is to train a feedforward nonlinear mapping model based on offline simulation or experimental data, taking the system state or disturbance information as input, and outputting the corresponding VSG optimization parameters or control gains, thereby achieving online adaptive parameter setting.

Radial basis function neural network is a three-layer feedforward network that uses Gaussian kernel function as the activation function of the hidden layer and is good at approximating nonlinear functional relationships. Yao et al. were among the first to apply the RBF neural network to the parameter adjustment of VSG. By taking the frequency deviation and its rate of change as input, they output the compensation amount of the virtual inertia and regularly adjusted the damping coefficient according to the size of the inertia [6]. This method demonstrates the feasibility of data-driven control. However, since only the output inertia and damping are linked according to empirical formulas, it is impossible to independently optimize the two, which limits the performance improvement. To address this deficiency, Ling et al. proposed using a multi-input and multi-output RBF network to simultaneously predict the optimal values of inertia and damping. The input includes system frequency deviation, power variation, etc., and can simultaneously output virtual inertia J and damping D that adapt to the current working conditions [7]. Compared with the fixed parameters, the RBF neural

network strategy has a significantly enhanced ability to suppress frequency disturbances - the peak frequency deviation is reduced and the recovery time is shortened. However, since this method relies entirely on offline data training, the network performs well only within the working conditions covered by the training data.

Supervised learning can also assist in control through short-term predictions of system dynamics. Lu Anyu et al. constructed a model combining convolutional neural networks with long short-term memory networks to predict the frequency variation trajectory of the power grid at several future moments after being disturbed [3]. Compared with the traditional VSG without pre-adjusting parameters, the adaptive control strategy adopting the CNN-LSTM prediction mechanism reduces the frequency fluctuation amplitude, and both the overshoot and steady-state error in the frequency modulation process are reduced. Its drawback is that model training requires a large amount of historical data under variable working conditions, and to ensure prediction accuracy, the model needs to be constantly updated or the network complexity increased.

3.2 Reinforcement learning

Early studies such as Zhang Kai et al. applied Q-learning to the VSG control of off-grid microgrids, and the results showed that Q-learning agents could effectively suppress low-frequency oscillations [8]. However, Q-learning requires the construction of a huge Q-table. Once the states and actions are discretized too finely, it will lead to a "dimensional disaster", making it difficult to deal with continuous space problems.

To address this issue, Wu et al. introduced the deep Q-network algorithm and used neural networks to approximate the Q-value function. They designed a VSG robust parameter adaptive control method based on DQN and verified its adaptability to parameter perturbation in the traction power supply system of electric vehicles [9]. This effectively reduces the storage requirements, but its action output is still a discrete set and cannot precisely adjust the continuous parameters.

Li et al. adopted the DDPG algorithm to achieve continuous control of the virtual inertia and damping of isolated island VSG [10]. The simulation results show that the DDPG intelligent machine can continuously adjust parameters under different load disturbances, minimizing frequency deviation and recovery time. However, DDPG is prone to being affected by estimation bias and may converge to suboptimal strategies.

To enhance the stability of DDPG, Oboreh-Snapps et al. introduced the double-delay deep deterministic Policy Gradient (TD3) algorithm for VSG control [11]. TD3 reduces the value estimation error by adopting a dual-Q network and a delayed update strategy, making the agent training more stable. This method has achieved good results in the frequency control of energy routers.

Lu et al. adopted the SAC algorithm to solve the optimal control strategy of VSG [4]. Under the free conditions of the model, they trained the agent only by interacting with the simulation environment and successfully found strategies to optimize inertia and damping, thereby improving the three goals of active power and frequency fluctuation as well as regulation time. This indicates that converting the VSG optimization problem into an RL task is feasible and effective.

In addition to the aforementioned single-agent RL, the exploration of multi-agent reinforcement learning (MARL) has also emerged in multi-inverter systems. Qiang Yang et al proposed a distributed dynamic inertia control strategy based on multi-agent deep reinforcement learning, enabling multiple parallel VSGs to coordinate and adjust their respective inertia and sagging coefficients, achieving group frequency synchronization and oscillation suppression [12]. This method utilizes the information exchange among agents to achieve better overall performance than single-machine optimization, providing a new idea for the collaborative control of multi-VSG systems.

Hao Shuai et al introduced a safety reinforcement learning algorithm with stability constraints and evaluated the action safety using the Lyapunov function to ensure that the RL agent always meets the system stability margin requirements during the learning process [13]. They verified this method in the frequency control of microgrids containing VSG, which can gradually optimize the control performance while ensuring stability.

3.3 Deep learning

Deep learning is a machine learning method represented by multi-layer neural networks, which is good at extracting complex feature relationships from massive amounts of data. In the field of VSG parameter optimization, deep learning mainly has two application directions: auxiliary decision-making and autonomous control.

Firstly, deep learning is used to assist in decision-making, that is, to establish deep prediction or evaluation models for complex systems, providing a basis for parameter optimization. Shen et al. constructed an online transient stability evaluation model using a long Short-Term memory network (LSTM), taking in the real-time operation data of the microgrid multi-VSG system and outputting the stability index or instability probability of the system under a given disturbance [14].

Secondly, deep learning is applied to autonomous control, that is, deep neural networks are used to directly output control instructions or replace some controllers. For instance, the controller designs based on deep feedforward neural networks and convolutional neural networks mentioned earlier all simulate the optimal control strategy by training a deep model offline, and then directly obtain the parameter adjustment values during runtime through network reasoning based on the measured quantities. Yang et al. designed a deep learning controller based on the double-delay deep deterministic policy gradient (TD3) algorithm in a modular multilevel converter (MMC) grid-connected system. This controller learned to directly output appropriate control signals from system measurements through offline training [15]. Compared with the classic VSG control, the new strategy offers better control performance in terms of frequency and voltage, with smaller oscillations and faster recovery.

It is also worth noting that deep learning and reinforcement learning are often combined to form deep reinforcement learning (DRL) methods. DQN, DDPG, SAC and others all belong to deep reinforcement learning because they internally use deep neural networks to approximate value functions or policy functions. Therefore, one of the most significant manifestations of deep learning in VSG control is actually achieving intelligent control through DRL.

In conclusion, deep learning plays a significant role in VSG parameter optimization through nonlinear mapping and predictive capabilities. It can not only serve as an intelligent auxiliary tool (predicting and evaluating system dynamics and identifying working conditions), but also directly act as an intelligent controller to participate in closed-loop control. Deep neural networks can handle high-dimensional complex inputs (such as multi-point measured voltage, current, and frequency data) and discover potential patterns within them, thereby overcoming the nonlinear and uncertain problems that traditional control systems find difficult to cope with. However, deep learning models usually lack physical interpretability and require a large amount of training data support. Their generalization ability and security reliability have also attracted much attention.

4 Method Comparison and Analysis

The characteristics of different machine learning methods in the adaptive control of VSG parameters vary. To visually compare the performance characteristics of several types of methods such as supervised learning, deep learning, reinforcement learning, and multi-agent reinforcement learning, Table 1 summarizes the main advantages and disadvantages of different methods.

Table 1. Advantages and Limitations of Various Methods.

Method type	Represent algorithms and application cases	Advantages and features	Limitations and Challenges
Supervised learning	Feedforward Neural Network, Support Vector Machine; RBFNN for inertia and damping adjustment, etc.	Simple principle and fast execution speed; Nonlinear relationships can be learned by using historical data. Easy to implement	Relying on the coverage of training data, it is difficult to generalize to unknown working conditions. Lack of online learning ability
Deep learning	CNN, LSTM, deep feedforward network; CNN-LSTM for frequency prediction, etc.	Strong expression ability, capable of extracting complex features; Applicable to time series prediction and high-dimensional problems; Its performance is superior to that of shallow models	The demand for data is large and the training cost is high. The model has a complex structure and poor interpretability

Reinforcement learning	Q-learning for multi-VSG frequency control; DDPG/SAC for parameter optimization, etc.	No need for precise models; online trial-and-error optimization strategies. It can adapt to dynamic changes and optimize multi-objective performance	The training process is complex and time-consuming, requiring a large amount of interactive sampling. It is necessary to design rewards reasonably to avoid bad strategies. Thorough simulation verification is required before deployment
Unsupervised learning	Principal Component Analysis (PCA); clustering methods.	It can assist in feature learning and be used for system state perception and fault detection	It is not the main learning method but only an auxiliary tool

In terms of real-time performance, supervised learning and deep learning, due to their direct mapping of output, have low computational overhead and are very fast in controlling execution, but they cannot self-correct policies during operation. Reinforcement learning agents also execute very quickly when deployed, and the strategy itself takes into account the dynamic evolution of the system, thus being more robust when the environment changes. However, the training process for obtaining this strategy is relatively slow and not suitable for frequent online retraining. In terms of generalization, since all methods require data-driven training, whether it is supervision or reinforcement, there is a problem of performance degradation when the training-test distribution is inconsistent. Relatively speaking, deep learning has a large capacity and is expected to improve generalization performance through diversified training. If reinforcement learning agents cover various possible perturbations during training, the robustness of their strategies to unseen situations will also improve, but more research is still needed to completely solve generalization. In terms of implementation complexity and engineering application difficulty, traditional supervised learning is the simplest, followed by deep learning, while reinforcement learning, especially multi-agent methods, is the most complex, requiring a significant investment of computing power and professional knowledge to debug the algorithm. Therefore, when making practical application choices, it is necessary to combine the requirements of the power system for reliability and real-time performance and balance which intelligent methods to adopt. For instance, in scenarios where small disturbances occur frequently but the patterns are relatively fixed, priority can be given to training supervised learning models that are simple and responsive. In the face of scenarios with intense disturbances or highly uncertain models, reinforcement learning strategies may better guarantee performance, but they come at the cost of initial training and validation.

5 Challenges and future development directions

Although ML has made significant progress in VSG parameter adaptive control, it still faces multiple challenges in moving towards large-scale engineering applications. Firstly, the generalization and adaptation to unknown working conditions are insufficient. The model often performs well within the training domain but fails when it exceeds the boundary. Migration/domain adaptation needs to be introduced to quickly fine-tune the trained model to the new system. Develop incremental and lifelong learning, and update online with new data without forgetting. Combining simulation and measured data enhancement to broaden the boundaries of cognition. Secondly, the training cost is high, and deep (reinforcement) learning often relies on a large amount of interaction and repeated trials. Model-based RL can be used to reduce real-world interaction and guide strategy updates with model predictions. Parallel/distributed training accelerates convergence; Develop small data learning and meta-learning, and integrate physical mechanisms to compress the search space. Thirdly, physical integration and interpretability promote physically guided ML, incorporating grid equations, stability constraints, and parameter boundaries into the network structure or loss/reward. At the same time, enhance interpretability by using sensitivity visualization, small-signal equivalence models, rule/tree distillation, etc. Fourth, the responsibility differentiation under machine decision-making: If problems occur after adjusting the parameters judged by AI, who should be held responsible? AI itself does not have the ability to be held accountable for errors. The detailed responsibility differentiation system is questionable.

6 Conclusion

This article reviews the progress of ML in the adaptive control of VSG parameters. VSG enhances the frequency stability of high-permeability new energy systems through virtual inertia and damping, but fixed parameters are difficult to adapt to complex working conditions. ML offers new approaches. Supervised/deep learning is used for rapid estimation of participation in dynamic modeling, reinforcement learning optimizes strategies through interaction, and multi-agent support for collaborative control. However, both have their advantages and disadvantages. The former relies on offline data, the RL training cost is high, and the MAS implementation is complex. The implementation of the project is still constrained by factors such as generalization, real-time performance, safety and responsibility attribution. In the future, efforts should be made to enhance generalization robustness and training efficiency, integrate knowledge of electrical physics to improve interpretability and credibility, and gradually verify through digital simulation and experiments. With the development of transfer learning, physical guidance and multi-agent collaboration, intelligent VSG is expected to provide important support for the safety and stability of power grids.

References

1. W. Breesam, R. Alamian, N. Tashakor et al., Frequency control in microgrids: An adaptive fuzzy-neural-network virtual synchronous generator. *arXiv eess.SY*, arXiv:2506.18611 (2025).
2. M.R. Ghodsi, A. Tavakoli, A.S. Far, Microgrid stability improvement using a deep neural network controller based VSG. *International Transactions on Electrical Energy Systems* 2022, 7539173 (2022).
3. A. Lu, G. Zeng, J. Zhao et al., Adaptive control strategy for inertia damping of virtual synchronous generator based on CNN-LSTM. *Journal of Wuhan University (Natural Science Edition)* **50**(6), 579–588 (2024).
4. C. Lu, X. Zhuan, Adaptive control for virtual synchronous generator parameters based on soft actor critic. *Sensors* **24**, 2035 (2024).
5. Y. LeCun, Y. Bengio, G. Hinton, Deep learning. *Nature* **521**, 436–444 (2015).
6. F. Yao, J. Zhao, X. Li et al., RBF neural network based virtual synchronous generator control with improved frequency stability. *IEEE Transactions on Industrial Informatics* **17**(6), 4014–4024 (2021).
7. Z. Ling, Y. Liu, Z. Wang et al., Adaptive inertia and damping of grid-connected inverter with improved VSG control. *IET Power Electronics* **16**(16), 2473–2480 (2023).
8. K. Zhang, et al., A virtual synchronous generator control strategy with Q-learning to damp low frequency oscillation, in *Asia Energy and Electrical Engineering Symposium (AEEES)*, (Chengdu, China, 2020), pp. 111–115.
9. W. Wu, et al., Deep Q-network based adaptive robustness parameters for virtual synchronous generator, in *IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific)*, (Hangzhou, China, 2022), pp. 1–4.
10. Y. Li, et al., Data-driven optimal control strategy for virtual synchronous generator via deep reinforcement learning approach. *Journal of Modern Power Systems and Clean Energy* **9**(5), 919–929 (2021).
11. O. Oboreh-Snapps, et al., Virtual synchronous generator control using twin delayed DDPG method. *IEEE Transactions on Energy Conversion* **39**(2), 214–228 (2023).
12. Q. Yang, et al., A distributed dynamic inertia-droop control strategy based on multi-agent deep reinforcement learning for multiple paralleled VSGs. *IEEE Transactions on Power Systems* **38**(6), 5598–5612 (2023).
13. S. Hao, et al., Safe reinforcement learning for grid-forming inverter based frequency regulation with stability guarantee. *Journal of Modern Power Systems and Clean Energy*, Early Access (2024).
14. Y. Shen, Z. Shuai, C. Shen et al., Transient angle stability prediction of virtual synchronous generator using LSTM neural network, in *IEEE Energy Conversion Congress and Exposition (ECCE)*, (Vancouver, BC, Canada, 2021), pp. 3383–3387.
15. M. Yang, X. Wu, M.C. Loveth, A deep reinforcement learning design for VSGs accommodating MMC. *Applied Sciences* **13**(10), 5879 (2023).

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