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Time series generative adversarial network controller for long-term smart generation control of microgrids

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A B S T R A C T

The conventional combined generation control framework of microgrids, which contains two time-scales, i.e., the time slot of economic dispatch is set to 15 min; and the total time slot of smart generation control and generation command dispatch is set to 4 s, could lead to uncoordinated problems. To avoid uncoordinated problems, this paper proposes a long-term smart generation control framework with a single time-scale to replace the conventional combined generation control framework with two time-scales, and then proposes time series generative adversarial network controller for long-term smart generation control of microgrids. The proposed time series generative adversarial network controller contains reinforcement learning, generator deep neural networks, and discriminator deep neural networks. The generator deep neural networks generate predicted states from multiple historical states, multiple historical actions, and multiple long-term actions. The discriminator deep neural networks judge whether the data from the generator deep neural networks or real-life data. This paper compares the proposed controller with conventional optimization algorithms and control algorithms, which are applied for economic dispatch, smart generation control, and generation commands dispatch in microgrids. The numerical simulation results under Hainan Power Grid, IEEE 300-bus power system, and IEEE 1951-bus power system verify that the proposed time series generative adversarial network controller can simultaneously obtain higher control performance and smaller economic cost than conventional combined control algorithm and optimization algorithms in the long-term. Consequently, the uncoordinated problem of economic dispatch, smart generation control, and generation commands dispatch can be solved by the proposed approach with one single long-term time-scale.

1. Introduction

Numerous distributed renewable sources [1] have been connected into smart grids [2] or microgrids [3], such as wind power [4] and photovoltaic power [5]. To mitigate the intermittent effects and improve the control performance [6] of microgrids, several control strategies applied to microgrids,including e.g. droop control [7], single master operation and multi master operation [8], and developed a multi-agent decentralized energy management system [9]. Recently, smart generation control (SGC) has been proposed to replace automatic generation control (AGC) [10]. Compared with the AGC, the SGC has higher intelligence [11]. The major features of the SGC can be summarized as: (1) the SGC can obtain high control performance; (2) the SGC can obtain multiple optimal optimization objectives simultaneously; (3) the SGC controllers can obtain high control performance for every controlled area in the power system if each controlled area has one SGC controller [12].

Generally, both the balance of active power flow and the frequency deviation of power systems are not only controlled by the SGC controller of microgrids but also economic dispatch (ED) [13]. Furthermore, the generation command for multiple SGC units (such as turbine generators and hydropower units) in a microgrid should be dispatched by generation commands dispatch (GCD) [14]. Therefore, both the ED and the GCD of power systems are optimized by optimization algorithms, such as particle swarm optimization (PSO) [15] and genetic algorithm [16]; the SGC can be controlled by a controller, such as proportional–integral–derivative (PID) controller [17] and reinforcement learning based controller [18]. Moreover, ED, SGC, and GCD are optimized or controlled with multiple time-scales. The total time slot of the SGC and the GCD of microgrids is few seconds, 4 s to 8 s in general; such as the time slot of microgrids in China Southern Power Grid is set to 4 s [19]. While the time slot of the ED can be configured as 4 h, 1 h, or 15 min [20]. These programming for ED, SGC, and GCD are combined to reduce the frequency deviation of power systems in general [21]. However, the conventional combined

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framework of power systems has three deficiencies [22]: (1) the optimization objectives of ED and GCD (economic objective) are different from the control objective of SGC (control performance objective); (2) the generation command from ED could be contrary to the generation command from SGC; for example, the generation command from ED is to reducing economic cost, while the generation command from SGC is to reducing frequency deviation; (3) the generation command for optimized economic objective could be caused low control performance and large frequency deviation.

To mitigate these three deficiencies of the conventional combined framework, a long-term smart generation control (LTSGC) framework is proposed to replace the conventional combined framework in this paper. Since the time slot of ED (15 min) is far larger than the time slot of SGC and GCD (4 s), the long-term historical information (i.e., historical systemic load) is considered in the programming of ED. Since the LTSGC framework considers historical reward values, historical actions, and historical systemic states with a long-time slot, which can replace the conventional combined framework (combined with "ED+ SGC+ GCD"). The major features of the proposed LTSGC can be summarized as (1) the LTSGC controller should simultaneously provide multiple outputs for the SGC units of a microgrid; (2) the LTSGC framework should consider the historical information which is considered by the ED programming; (3) the control performance obtained by the LTSGC controller should be higher than the control performance obtained by the conventional combined controller; besides, the economic objective obtained by the LTSGC controller should be smaller than the economic objective obtained by the conventional combined optimization algorithm.

Various artificial intelligence algorithms have been applied to the ED, the GCD, and the SGC. Examples for SGC: the pure reinforcement learning algorithm can obtain higher control performance than conventional PID for the AGC of large-scale interconnected power systems [23]; since reinforcement learning has a simple structure and can update control strategy on-line, the reinforcement learning algorithm can be improved as Q(λ) learning [24], an evolutionary reinforcement learning algorithm [25], and transfer reinforcement learning algorithm [26]. With the development of deep learning, reinforcement learning and deep learning are combined as deep reinforcement learning [27]; the deep reinforcement learning has been proposed for the SGC of power systems with varying systemic inner parameters [11]. Moreover, multiple deep neural networks (DNNs) and relaxed operation are combined as a relaxed deep learning algorithm, which has been applied to replace the combined framework with "unit commitment + ED + SGC + GCD" in large-scale interconnected power systems [22]. Examples for ED and GCD: numerous biologically inspired algorithms and swarm behavior inspired have been applied to optimization problems, such as gray wolf optimizer [28] and grouped gray wolf optimizer [29]. However, these reinforcement learning algorithms can only update the control strategy with real-time reward value and immediate systemic state; besides, these inspired optimization algorithms should be highly matched with the optimization problem. Otherwise, these inspired optimization algorithms could not obtain a globally optimized solution.

To obtain high control performance and economically for the LTSGC of microgrids, a time series generative adversarial network (TSGAN) controller is proposed for the LTSGC of microgrids in this paper. The TSGAN contains reinforcement learning and deep generative adversarial networks (DGANs). Generative adversarial networks (GANs) have been proposed by Goodfellow et, al. at the year of 2014 [30]. Since the GANs has the outstanding generating ability, the GANs is not only applied for various types of images and natural language data but also inspires and promotes the development of semi-supervised and unsupervised learning [31]. In recent years, artificial intelligence has become a hot topic, and the emergence of AlphaGo has greatly developed deep learning [32]. Numerous deep learning usually supervised learning (e.g. logistic regression, backpropagation neural networks and, DNNs, etc.) [33], which require abundant manpower and material resources to be labeled. While the GANs can generate data for its self; i.e., the data does not need to be labeled [34]. The major features of the GANs can be summarized as (1) the model of GANs is applied for backpropagation, and does not need Markov chain; (2) the GANs does not need to infer hidden variables when the GANs is trained, and the generator and discriminator of GANs can be built by differentiable functions; (3) the parameter updated process of the generator of the GANs is based on the backpropagation of the discriminator of the GANs. The TSGAN constructs a min–max game system to generated sequence simulation data to simulate real data. Therefore, the amount of time series data is applied to the TSGAN to generate systemic load data. And the major contributions of this paper can be summarized as (1) the conventional combined generation control framework with multiple time-scales of microgrids is replaced by a controller with one single time-scale; (2) the proposed method simultaneously considers the historical reward values and historical systemic states in the long-term rather than immediate reward value and immediate systemic state; (3) both the control performance and the optimization performance of microgrids are simultaneously considered for one real-time controller rather than a divided control algorithm and optimization algorithm.

This paper adopts the TSGAN controller for the LTSGC control framework of microgrids with the following prominent features.

1. With the DNNs is introduced into the TSGAN, the TSGAN can improve accuracy, stability, and control performance for the LTSGC of the microgrids; with the data generated by the TSGAN is similar to real-life data, the TSGAN can improve the generation capacity of microgrids.
2. Since the reinforcement learning is introduced into the TSGAN, the TSGAN can process discrete sequence data by the generator G differentiation problem with directly performing gradient policy.
3. The TSGAN controller simultaneously considers historical information and system states; besides, the LTSGC framework can replace the combined "ED+SGC+GCD" framework, and the uncoordinated problems between the control algorithm and optimization algorithms of the generation control problem of microgrids can be solved by the proposed approach.

The rest of the paper is organized as follows: Section 2 introduces long-term smart generation control of microgrids. In Section 3, the proposed time series generative adversarial network controller is presented. The simulation results are displayed in Section 4. Section 5 briefly concludes this paper.

2. Long-term smart generation control of microgrids

2.1. Conventional generation control framework of microgrids

The conventional generation control framework of microgrids contains two-time slots, i.e., the long time slot for the ED, and short slot for the SGC and GCD.

The time slot of ED is set to 15 min in general. The optimization objectives of ED consist of three objectives, i.e., economic objective, carbon emission objective, and network losses objective in general. Therefore, the total of optimization objective function can be calculated as follows,

$$\min F_{\text{total}} = \omega_{\text{e}} F_{\text{total}}^{\text{e}} + \omega_{\text{c}} F_{\text{total}}^{\text{c}} + \omega_{\text{k}} F_{\text{total}}^{\text{k}}$$

$$F_{\text{total}}^{\text{e}} = \sum_{j=1}^{J_i} F_j^{\text{e}}\left(P_j\right) = \sum_{j=1}^{J_i}\left(c_j P_j^2 + b_j P_j + a_j\right)$$

$$F_{\text{total}}^{\text{c}} = \sum_{j=1}^{J_i} F_j^{\text{c}}\left(P_j\right) = \sum_{j=1}^{J_i}\left(\alpha_j P_j^2 + \beta_j P_j + \gamma_j\right)$$

$$F_{\text{total}}^{\text{k}} = \sum_{j=1}^{J_i} P_j - PD_i \tag{1}$$

$$\text{s.t.}\begin{cases} P_j^{\min} \le P_j \le P_j^{\max} \\ P_{j,t} - P_{j,t-1} \le P_j^{\text{up}} \\ P_{j,t-1} - P_{j,t} \le P_j^{\text{down}} \\ 0 < \omega_{\text{e}}, \omega_{\text{c}}, \omega_{\text{k}} < 1 \\ \omega_{\text{e}} + \omega_{\text{c}} + \omega_{\text{k}} = 1 \end{cases}$$

where ω_{e}, ω_{c} and ω_{k} are the weights of the economic objective, carbon emission objective and network losses objective of ED, respectively; $F_{\text{total}}^{\text{e}}$, $F_{\text{total}}^{\text{c}}$ and $F_{\text{total}}^{\text{k}}$ are the total objective values of the economic objective, carbon emission objective and network losses objective of ED, respectively; $P_j^{\max}$ and $P_j^{\min}$ are the maximum and the minimum active power flow of the jth SGC units, respectively; P_j^{up} and P_j^{down} are the maximum and the minimum active power flow of the jth SGC units between two control periods, respectively; $P_{j,t}$ is the active power flow of the jth generation unit at the tth time slot; a_j, b_j and c_j are the jth coefficients of the economic objective of ED; α_j, β_j and γ_j are the jth coefficients of the economic objective of ED; PD_i is the predicted active power flow of the microgrid.

The total time slot of SGC and GCD is set to 4 s in general. The optimization objective of the GCD is to minimize the economic objective of the ED in the conventional generation control framework of microgrids. The control objective of the SGC controller aims to minimize the frequency deviation of the microgrid and area control error (ACE) of active power flow. The "SGC and GCD" can provide multiple generation commands for the multiple SGC units of the microgrid (Fig. 1). In Fig. 1, Δf_i is the frequency deviation of the jth area; $T_{\text{g}ni}$, $T_{\text{t}ni}$ and T_{p} are the time constants of the governor, turbine generator and frequency response, respectively; B_i is the frequency basic factor of the microgrid; $\Delta P_{\text{tie}-i}$ is the active power flow deviation from other connected control areas; K_{p} is the system gain of the microgrid; R_n add is the frequency response coefficient of the nth generator in the area; $\Delta P_{\text{C}i}$ is the output of the controller.

Therefore, the major deficiencies of the conventional combined generation control framework are that, (1) since the optimization objectives of the ED and the GCD are different in general, the configuration of ED programming with optimal total objective could cause higher economic objective for GCD programming; (2) since the optimization objectives are different from the control objective in general, the configuration of the conventional controller with the smaller frequency deviation could cause higher economic costs.

2.2. Long-term smart generation control framework of microgrids

To mitigate the major deficiencies of the conventional combined generation control framework, the LTSGC is proposed for microgrids. Compared with the conventional combined generation control framework, the LTSGC replace the combined "ED + SGC + GCD" framework (Fig. 2). Therefore, the LTSGC is a framework with a unified time-scale; and the control time period of the LTSGC equals the total time slot of the SGC and the GCD, i.e., 4 s. Besides, the LTSGC controller should provide multiple generation commands for SGC units simultaneously.

2.3. Training process of time series generative adversarial network controller

The reward function and historical data are applied to the generator G. The proposed TSGAN simultaneously considers the historical reward values and historical systemic states in the long-term rather than immediate reward value and immediate systemic state. The generator deep neural network generates predicted states from multiple historical states, multiple historical actions, and multiple long-term actions. That is to say, "historical reward" is feeding into the training process of the proposed DGANs approach. The generator G and discriminator D gamble mutually; the generator G improves its performance through the signal from the discriminator D. Finally, the generator G can generate data, which is similar to real-life data. The real-life data means multiple historical, multiple historical actions, and multiple long-term actions in this paper. The training process of the DGANs of the TSGAN contains off-line training process and on-line training process (Fig. 3). For example, the current state is set to be Δf_t, $e_{\text{ACE}(t)}$; the historical states can be presented as $\Delta f_{(t-4)}$, $e_{\text{ACE}(t-4)}$, $\Delta f_{(t-8)}$, $e_{\text{ACE}(t-8)}$, $\ldots$, $\Delta f_{(t-40)}$, $e_{\text{ACE}(t-40)}$, $\ldots$, $\Delta f_{(t-400)}$, $e_{\text{ACE}(t-400)}$; the historical actions can be described as $a_{(t-4)}$, $a_{(t-8)}$, $\ldots$, $a_{(t-40)}$; the long-term actions can set to be $a_{(t-44)}$, $a_{(t-48)}$, $\ldots$, $a_{(t-400)}$, $\ldots$, $a_{(t-4000)}$. The off-line training samples for the DGANs of the TSGAN are obtained from conventional optimization algorithms and conventional control algorithms. The on-line training samples for the DGANs of the TSGAN are obtained from the real-time data on-line.

For the off-line training procedure, GANs have some deficiencies, such as unstable training, gradient disappearance, and model collapse. To increase the convergence rate of each agent, the agent should be off-line training at first; the samples for DGANs of the TSGAN in the off-line training procedure can be obtained with considering the historical states, historical actions, and long-term actions act as the inputs of the DGANs; the states of next time act as the outputs of the DGANs. For the on-line training procedure, the samples for the discriminator D of the TSGAN considering the historical states, historical actions, and long-term actions act as inputs, the stochastic noise and state act as the inputs of the generator G; and the action of the next time act as the output of the TSGAN. Moreover, the historical states, historical actions, and long-term actions are calculated by conventional optimization algorithms and conventional control algorithms. The reinforcement learning of TSGAN can be calculated as follows, (1) obtain information (Δf and e_{ACE}) from area i; (2) calculate state s and reward value; (3) updated Q-value matrix and P-value matrix; (4) select an action and generate actions matrix A.

3. Training process of time series generative adversarial network controller

Since the amount of prior knowledge is needed for microgrids, the parameters of conventional control algorithms and conventional optimization algorithms for microgrids are difficult to update. In Fig. 4, the agent selects the actions A according to the strategy in the current state s; the interconnection system receives the actions A and transition to the next state; the agent receives the reward value and back from the interconnection system; the agent selects the next action according to the strategy. The reinforcement learning of the TSGAN can provide interactions between the agent and the environment; the inputs of the reinforcement learning of the TSGAN are set to be frequency deviation and area control error, and the output of the reinforcement learning of the TSGAN is set to action for the SGC unit. While a min–max function is introduced, the GANs can generate the amount of data for the configuration of microgrids. The mode collapse could occur for the conventional GANs [35], a deep structure is applied to the GANs for the historical time series data of microgrids in this paper. Besides, a reinforcement learning framework is introduced into the GANs with deep structure, i.e., TSGAN is proposed in this paper. The proposed

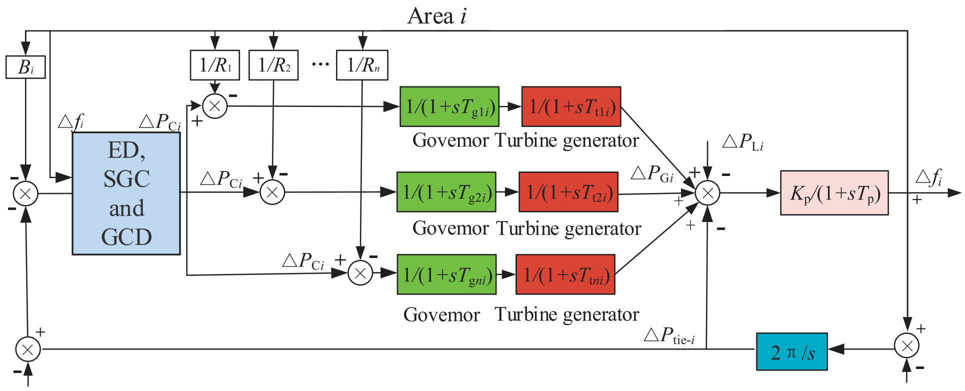


Fig. 1. Dispatch and control framework of conventional smart generation control.

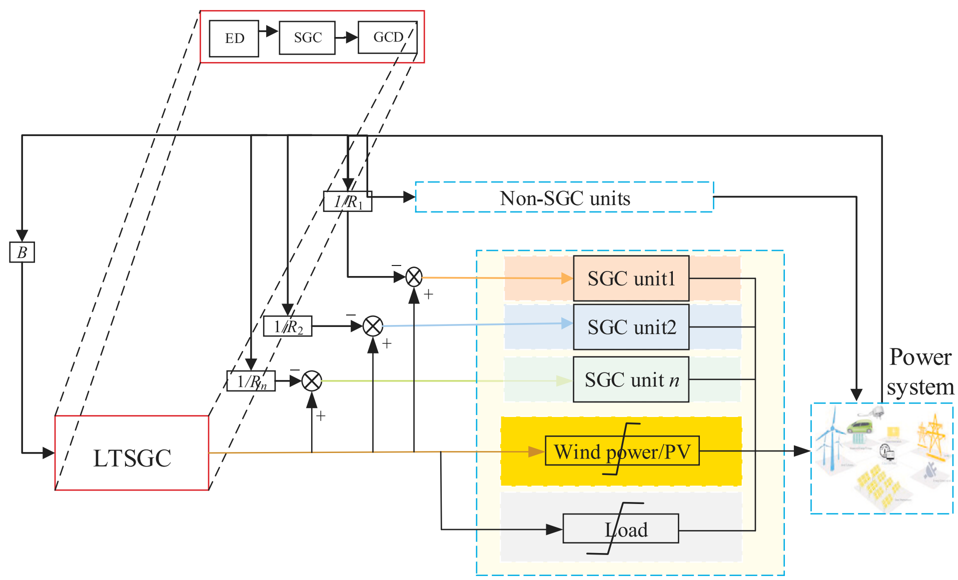


Fig. 2. Framework of the proposed long-term smart generation control.

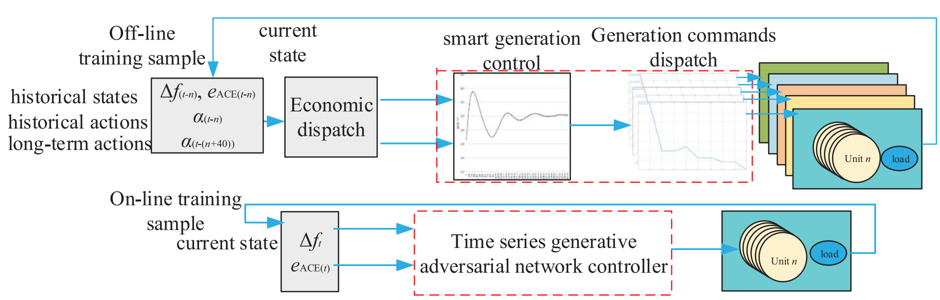


Fig. 3. Training sample for time series generative adversarial network controller.

TSGAN controller contains reinforcement learning and DGANs (Fig. 4). The structure of the DGANs is given in Fig. 5.

The reinforcement learning of the TSGAN can update control the strategy on-line with the updating of the Q matrix and the probability matrix, which can be updated as follows,

$$Q(s,a) \leftarrow Q(s,a) + \alpha(R(s,s',a) + \gamma \max_{a \in A} Q(s',a) - Q(s,a)) \tag{2}$$

$$P(s,a) \leftarrow \begin{cases} P(s,a) - \beta(1 - P(s,a)), & \text{if } a' = a \\ P(s,a)(1-\beta), & \text{if } a' \neq a \end{cases} \tag{3}$$

where s and s' are the current state and the next state of the system, respectively; α, β and γ are the learning rate, probability coefficient and reward coefficient of reinforcement learning of the TSGAN, respectively; $Q(s,a)$ and $P(s,a)$ are the Q-value and P-value matrices of reinforcement learning of the TSGAN, respectively; $R(s,s',a)$ is the reward value from the state s to the state s' with the action a; A is the action set for the reinforcement learning. The number of actions in actions set and the number of states in states set can be configured as the same. For instance, the number of states of the reinforcement learning of the TSGAN is set to be 11. Besides, the states range of the reinforcement learning of the TSGAN is set to be $\underbrace{(-\infty,-0.03),[-0.03,-0.023),\ldots,[0.023,0.03),[0.03,\infty)}_{11}$. The reward function of the reinforcement learning of the TSGAN should be dependent

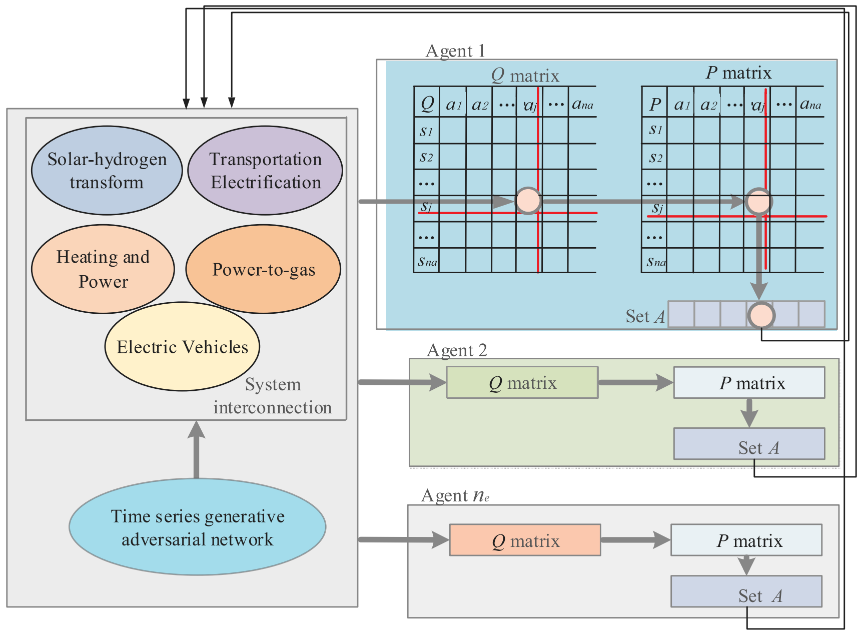


Fig. 4. Framework of time series generative adversarial network controller.

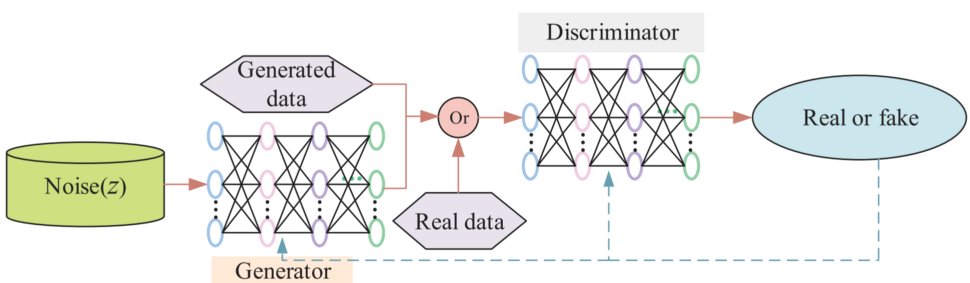


Fig. 5. Structure of deep generative adversarial networks.

on real applications. For example, the reward function of the reinforcement learning of the TSGAN for the LTSGC in this paper is designed as follows,

$$R(s, s', a) = -100|\Delta f|^2 - |e_{\mathrm{ACE}}|^2 \tag{4}$$

where e_{ACE} is the active power ACE of the controlled area.

Therefore, the inputs of the reinforcement learning of the TSGAN are set to be frequency deviation and area control error; and the output of the reinforcement learning of the TSGAN is set to action for SGC units. Since the training process of reinforcement learning can be configured as an on-line training process, the training data of reinforcement learning is real-time data obtained from microgrids.

The DGANs of the TSGAN contain two DNNs (Fig. 5), i.e., generator DNNs G and discriminator DNNs D. The DNNs in the TSGAN are trained by restricted Boltzmann machines (RBMs). The activation function of the RBM can be set as the "Levenberg–Marquardt" algorithm. More details about the energy system of the RBM can be found in [22]. The purpose of the generator G is to train a generating model G with the giving random noise vector Z (Fig. 5). The discriminator DNNs D judges whether the data from the generator DNNs G or real data, and finally generator DNNs G generates a sample consistent with the real data distribution $P_{\mathrm{data}(x)}$. The $G(z)$ generates data for the generator of the DGANs of the TSGAN. The Noise(z) generates noise data for the generator G of the TSGAN. After training iteration, generator G can generate data that can be similar to the real data.

The generator model G and the loss function of the discriminator D can be presented as follows,

$$\begin{cases} F_G(z) = D(G(z)) \\ F_D(x, z) = D(x) + \max{}^*(\partial - D(G(z))) \end{cases} \tag{5}$$

where x is sample data; $G(z)$ is generated data; ∂ is constant coefficient, which can be set to 0.5; z is the noise.

The training process of the TSGAN can be configured as a min–max optimization process,

$$\min_G \max_D V(G, D) = E_{x\sim P_{\mathrm{data}}}[\log D(x)] + E_{z\sim P_{\mathrm{G}}}[\log(1 - D(x))] \tag{6}$$

where x is the sample from the real data probability $P_{\mathrm{data}}(x)$; z is the sample from the prior distribution P_{G}; $E(\bullet)$ is the calculation expected value.

The parameters of the discriminator D can be updated by stochastic gradient descent as follows,

$$\nabla_{\theta,d} \frac{1}{k} \sum_{i=1}^{k} [\log D(x^{(i)}) + \log(1 - D(G(z^{(i)})))] \tag{7}$$

where k is the number of the small batch samples from real data.

The parameters of the generator G can be updated as follows,

$$\nabla_{\theta} \frac{1}{k} \sum_{i=1}^{k} \log(1 - D(G(z^{(i)}))) \tag{8}$$

Table 1
Parameters of conventional combined generation control framework.

Programming	Algorithm	Parameters	Values
ED	PSO	Population size	300
ED	PSO	Maximum iteration	100
ED	Genetic algorithm	Population size	300
ED	Genetic algorithm	Maximum iteration	100
SGC	Reinforcement learning	α, β, γ	$\alpha = 0.1$, $\beta = 0.05$, $\gamma = 0.9$
SGC	Reinforcement learning	Actions set A	{−300, −240, −180, −120, −60, 0, 60, 120, 180, 240, 300}
SGC	PID	Proportional	−0.006
SGC	PID	Integral	0.0004
SGC	PID	Derivative	0
GCD	PSO	Population size	200
GCD	PSO	Maximum iteration	50
GCD	Genetic algorithm	Population size	200
GCD	Genetic algorithm	Maximum iteration	50
ED and GCD	PSO	Inertia coefficient	1
ED and GCD	PSO	Damping ratio of inertia coefficient	0.99
ED and GCD	PSO	Personal acceleration coefficient	2
ED and GCD	PSO	Social acceleration coefficient	2

3.1. Time series generative adversarial network controller for long-term smart generation control

The calculation steps of the TSGAN controller for the LTSGC of microgrids are shown in Fig. 6. The TSGAN controller contains reinforcement learning and DGANs. The time series data should preserve temporal dynamics and attend to the temporal correlations unique. In the TSGAN, the generator G can be regarded as an agent in reinforcement learning; the states of TSGAN are the current e_{ACE} and Δf, and the action value is the generation command for the SGC units at the next time; besides, the purposed training discrimination D aims to guide the direction of generator learning. The inputs for the discriminator D consist of real-life data and generated data; and the discriminator D is updated with reward values by reinforcement learning. The purposed of calculating the reward value aims to confuse the discriminator D; and the discriminator D misapprehension that the data generated by the generator is real-life data. In Fig. 6, the inputs of the TSGAN are set to be frequency deviation and area control error; and the output of the TSGAN is set to action for the SGC unit. The discriminator D has two inputs sources, i.e., the real data from reinforcement learning and the generated data from generator G, which aims to distinguish between the two sources.

The conventional GANs applied of microgrids could lead to two major deficiencies, (i) training the generator G should be input the data at the same time; (ii) the discrete data from the generator G of TSGAN make it difficult to pass the gradient update from the discriminator D. Therefore, the TSGAN controller is proposed to mitigate these two deficiencies. The TSGAN bypasses the generator G differentiation problem by directly performing gradient policy update [36]. The data of microgrids are complex, and the computation required to fit the model is large. However, the TSGAN constructs a min–max game system to generate sequence simulation data to simulate real-life data, which can solve the problem of insufficient samples of the microgrid.

The pseudo-code of the TSGAN controller is given in Algorithm 1. The TSGAN controller can provide multiple outputs generation commands for the multiple SGC units of the microgrid. The set matrix A of the "Generate actions" of Fig. 6 is a $n \times m$ generation commands matrix, which can be presented as follows,

$$A = [A1,\ A2,\ \dots,\ An] = \begin{pmatrix} a_1^1 & \cdots & a_n^1 \\ \vdots & \ddots & \vdots \\ a_1^m & \cdots & a_n^m \end{pmatrix} \tag{9}$$

where n is the number of actions in an action pool, and n is set to be 10^6 in this paper; m is the number of SGC units. For the specific LTSGC problem of microgrids, the inputs of the LTSGC are set as Δf, e_{ACE}; the outputs of the LTSGC are set to generation commands ΔP_{G} for SGC units in microgrids.

Algorithm 1: Pseudo code of time series generative adversarial network.

1: Initialize parameters (learning rate α, probability coefficient β, reward coefficient γ, the number of the small batch samples k, the number of actions in an actions pool n and the number of SGC units m)
2: Initialize matrices (Q-value matrix, P-value matrix and generation commands matrix A)
3: **while** The system is running **do**
4: Obtain systemic states (frequency deviation Δf and area control error e_{ACE}) from microgrids with Fig. 1
5: Calculate reward value by Eq. (4)
6: Update Q-value matrix by Eq. (2)
7: Update P-value matrix by Eq. (3)
8: Select action by reinforcement learning
9: Generate actions matrix A by Eq. (9)
10: Generate data by generator DNN with Eqs. (5)-(8)
11: Judge action between generator DNN and reinforcement learning by discriminator DNN with Eqs. (5)-(8)
12: Select the action value with the highest probability by Eqs. (5)-(6)
13: Calculate systemic values with Fig. 1 and go to Step 3

4. Numerical simulations

The proposed TSGAN is compared with conventional combined algorithms under three cases, i.e., Hainan Power Grid, IEEE 300-bus power system, and IEEE 1951-bus power system. All the programming of Simulink/MATLAB in this paper is simulated on MATLAB R2019b in a personal computer with i7-7700 3.6 GHz CPU and 16 GB RAM.

The parameters of conventional algorithms of conventional combined generation control framework are given in Table 1. The training data for the TSGAN of these three cases are obtained from conventional algorithms with 86,400 s configured simulation time. The training time and calculating time of the TSGAN in these three cases are given in Table 2. The calculating time of the TSGAN in all these three cases is lesser than the control period of microgrids (4 s).

4.1. Hainan power grid

In this case, the Hainan Power Grid, which is a part of China Southern Power Grid, contains 8 SGC units (Fig. 7) and wind power. The curves of the wind power and the systemic power load of this microgrid are shown in Fig. 8(a) and Fig. 8(b), respectively.

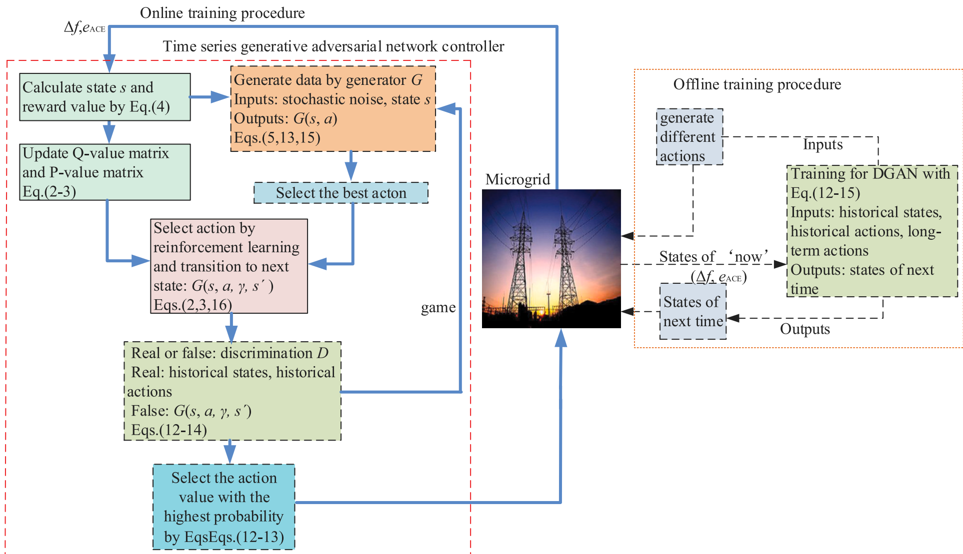


Fig. 6. Calculation steps of time series generative adversarial network controller.

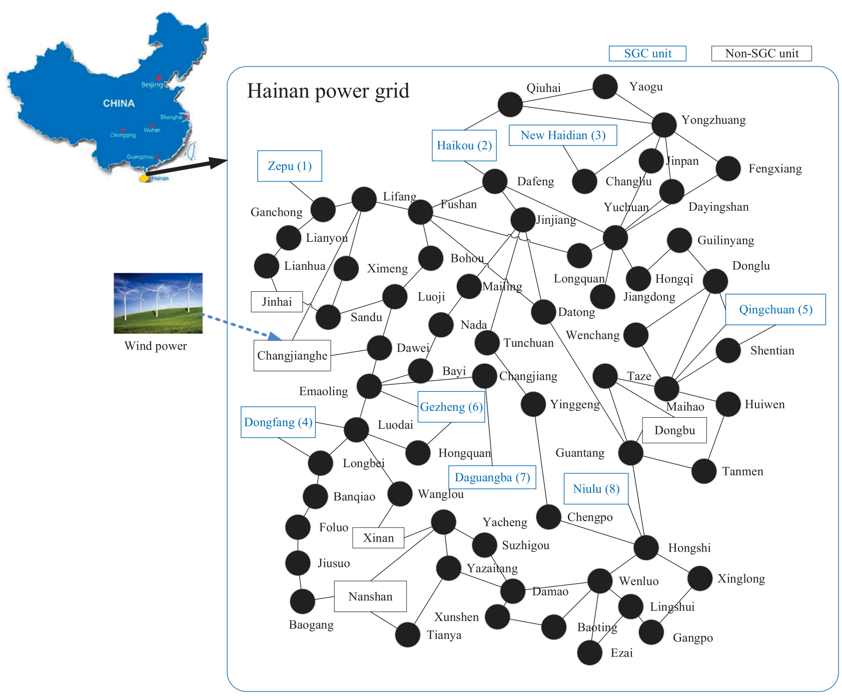


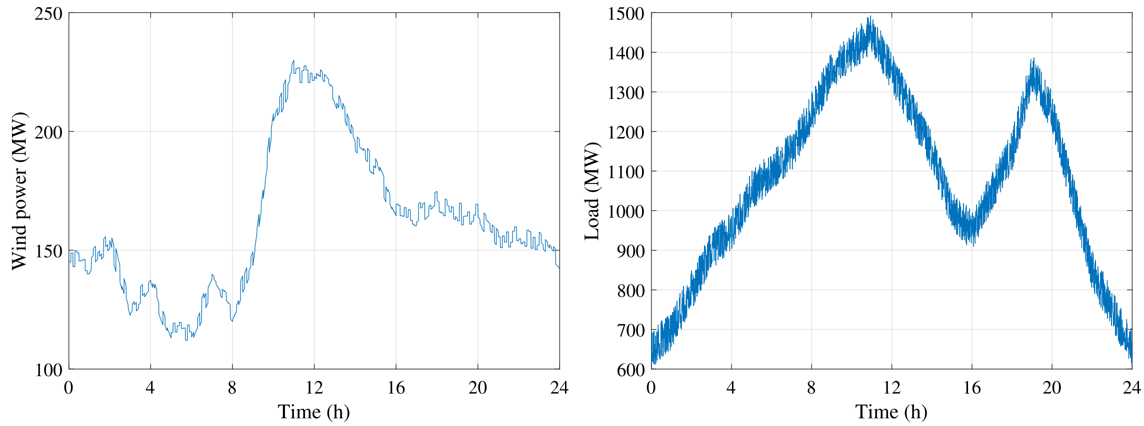
Fig. 7. Topology of Hainan Power Grid.

Table 2
Training time and calculating time of time series generative adversarial network in three simulated cases.

Power grid	Training time (s)	Calculating time (s)
Hainan Power Grid	3265.942	0.038
IEEE 300-bus power system	3577.032	0.041
IEEE 1951-bus power system	4544.661	0.526

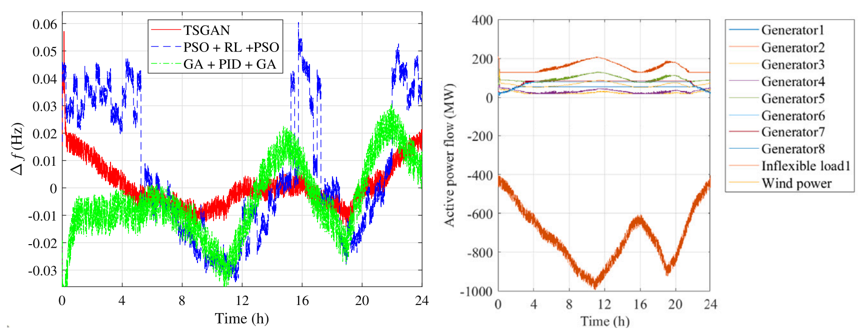
The total simulation time of each simulation, in this case, is set to be 86,400 s. The control period of the TSGAN based LTSGC controller is 4 s; that is to say, the TSGAN programming is run at the time of 0 s, 4 s, …, 86,400 s. The optimization period of the ED programming is 15 min; i.e., the ED programming is run at the time of 0 s, 900 s, …, 86,400 s. The total control period of the SGC and the GCD is 4 s; i.e., the SGC and the GCD are run at the time of 0 s, 4 s, …, 86,400 s. The number of layers of the DNNs of the TSGAN and the number of the hidden units of each layer of the DNNs of the TSGAN is set to be 6 and 91, respectively. The training process of the DNNs of the TSGAN is set to be Levenberg–Marquardt function. Besides, the learning rate of the DNNs of the TSGAN is set to be 0.00014 in this case. Other parameters of the Hainan Power Grid are given in Appendix.

The simulation results of this case obtained by conventional "ED + SGC + GCD" (i.e., PSO + reinforcement learning + PSO, genetic algorithm + PID + genetic algorithm) programming and the proposed TSGAN are given in Table 3. Since more accurate actions are given for SGC units in the microgrid, the larger value $P_i - PD_i$ (Eq. (1)) can be obtained by the TSGAN controller; therefore, the network loss cost obtained by the TSGAN is larger than that obtained by the conventional algorithms (Table 3). The frequency deviation obtained by simulated



(a) (b)

Fig. 8. Curves of wind power and systemic load: (a) wind power; (b) systemic load.



(a) (b)

Fig. 9. Frequency deviations and active power flows obtained by simulated algorithms in Hainan Power Grid: (a) frequency deviation Δf (Hz); (b) active power flow (MW).

algorithms in Hainan Power Grid is given in Fig. 9(a). The active power flow dispatched by the TSGAN in Hainan Power Grid is given in Fig. 9(b).

Simulation results obtained by the simulated algorithms in Hainan Power Grid (Table 3 and Fig. 9) show that (1) compared with the conventional control algorithm for SGC, the proposed TSGAN can obtain higher control performance with smaller frequency deviation in Hainan Power Grid; (2) compared with the conventional optimization algorithm for ED and GCD, the proposed TSGAN can obtain smaller optimization objective value with a smaller total cost in Hainan Power Grid; (3) compared with the conventional combined generation control framework, the proposed LTSGC has a compact structure; and the LTSGC with a unified time-scale can replace the conventional combined generation control framework in Hainan Power Grid.

After training the DGANs of TSGAN, the TSGAN controller can obtain high control performance and small objective value simultaneously. The TSGAN can provide multiple generation commands for multiple SGC units simultaneously. Furthermore, Table 3 shows that the coordinated problem of the conventional “ED + SGC + GCD” framework in microgrids can be solved by the TSGAN of LTSGC of microgrids.

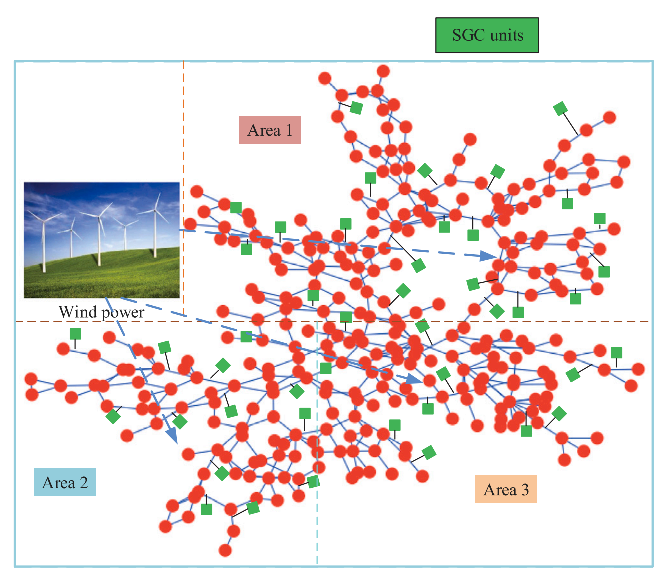


Fig. 10. Structure of microgrid based on IEEE 300-bus power system.

4.2. IEEE 300-bus power system

In this case, the IEEE 300-bus power system, which was obtained from Fernando Alvarado at the University of Wisconsin, is divided into 3 areas (Fig. 10) [37]. This microgrid is designed as a microgrid with 45 SGC units and 24 non-SGC units. Besides, the wind power (Fig. 8(a)) is connected to the microgrid. The systemic load curve of this case is designed as the same as Fig. 8(b), while the maximum value is 490 MW.

The numbers hidden layers and hidden units in each layer are set to be 3 and 91, respectively. The learning rate of the DNNs of the TSGAN is set to be 0.00023 in this case. Other parameters of the TSGAN is set

Table 3
Average frequency deviations, economic cost, coal cost, network loss costs and total costs obtained by simulated algorithms in Hainan Power Grid.

Algorithms	Average $\|\Delta f\|$ (Hz)	Economic cost ($)	Coal cost ($)	Network loss cost ($)	Total cost ($)
PSO + RL + PSO	0.0211	531293602.2066	6604732.8740	14352719.4104	184083684.8303
GA + PID + GA	0.0126	1787818991.9234	13211327.1413	29870723.2238	610300347.4295
TSGAN	**0.0063**	**362311103.8107**	**5860881.5157**	15350050.4564	**127840678.5943**

Bold indicates best values corresponding to that indices; GA=Genetic algorithm; RL=Reinforcement learning.

Table 4
Average frequency deviations, economic cost, coal cost, network loss costs and total costs obtained by simulated algorithms in IEEE 300-bus power system.

Algorithms	Average $\|\Delta f\|$ (Hz)	Average ACE (MW)	Economic cost ($)	Coal cost ($)	Network loss cost ($)	Total cost ($)
PSO + RL + PSO	0.0249	255.8150	2943825699.7479	37598835.0201	71978291.3369	1017800942.0350
GA + PID + GA	0.0404	263.7484	3492085894.5507	39904447.6096	60453714.5906	1197481352.2503
TSGAN	**0.0080**	**225.7515**	**2593010750.9595**	**33219608.6850**	81306518.3236	**902512292.6560**

Bold indicates best values corresponding to that indices; GA=Genetic algorithm; RL=Reinforcement learning.

Table 5
Average frequency deviations, economic cost, coal cost, network loss costs and total costs obtained by simulated algorithms in IEEE 1951-bus power system.

Algorithms	Average $\|\Delta f\|$ (Hz)	Average ACE (MW)	Economic cost ($)	Coal cost ($)	Network loss cost ($)	Total cost ($)
PSO + RL + PSO	0.0394	240.4658	13238728989.6931	155136440.2330	261552190.3078	4551805873.4113
GA + PID + GA	0.1013	350.6263	13157347500.5725	151678093.3229	540342092.9505	4616455895.6153
TSGAN	**0.0183**	**127.2545**	**10356589233.8945**	**128134344.4583**	300537132.4690	**3595086903.6072**

Bold indicates best values corresponding to that indices; GA=Genetic algorithm; RL=Reinforcement learning.

the same as the TSGAN for Hainan Power Grid. The simulation results obtained by the simulated algorithms in the IEEE 300-bus power system are given in Table 4 and Fig. 11.

The simulation results, in this case, show that (1) compared with the conventional combined generation control framework, the proposed LTSGC can obtain higher control performance and optimal objective value than the conventional control algorithm and conventional optimization algorithms; (2) since the generator G of the TSGAN can generate a load data similar to real systemic load, the TSGAN can provide generation commands for generation units of the IEEE 300-bus power system, and then obtains high control performance and optimal objective value simultaneously; (3) the uncoordinated problem between the control algorithm and optimization algorithm of the generation control of the IEEE 300-bus power system can be solved through the proposed TSGAN.

4.3. IEEE 1951-bus power system

In this case, the microgrid is based on the IEEE 1951-bus power system, which contains 166 SGC units and 225 non-SGC units. In addition, the wind power (Fig. 8(a)) is connected to the IEEE 1951-bus power system. This microgrid, which is from the alternating current power flow data of the French system, is divided into 5 control areas. The numbers of hidden layers and hidden units in each layer are set to be 4 and 91, respectively. The learning rate of the DNNs of the TSGAN is set to be 0.00035 in this case. The wind power curve and the systemic load of this case are set to the same as that of the Hainan Power Grid case. Other parameters of the TSGAN are set to the same as that of the Hainan Power Grid case.

The simulation results (Table 5 and Fig. 12) show that (1) since the TSGAN can obtain high control performance and optimal objective value, the proposed LTSGC framework can replace the conventional combined generation control framework; (2) after the training process of the reinforcement learning and the DGANs of TSGAN, TSGAN can be configured as the controller for the LTSGC of microgrids; (3) compared with the conventional combined generation control framework, the proposed TSGAN can generate numerous sequence simulation data to simulate real-life data.

After the training process of the TSGAN, the TSGAN can mitigate the intermittent effects of microgrids and mitigate the deficiencies of the conventional combined framework of microgrids. Under these three cases, the proposed LTSGC controller based on the proposed TSGAN can provide multiple generation commands for multiple SGC units of microgrids with higher control performance and smaller economic cost simultaneously. Therefore, the uncoordinated problem of generation control of microgrids can be solved by the LTSGC based on the TSGAN.

After numerous testing, (1) the learning rate range of the DNNs of the TSGAN in microgrids can be set as [0.00001, 0.001]; (2) the number of the hidden layers of the DNNs of the TSGAN can be larger than 2; (3) the number of hidden units of each layer of the DNNs of the TSGAN can be larger than 60. Furthermore, (1) the learning rate range of the reinforcement learning of the TSGAN can be set as [0.001, 0.1]; (2) the probability coefficient range of the reinforcement learning of the TSGAN can be set as [0.01, 0.04]; (3) the reward coefficient range of the reinforcement learning of the TSGAN can be set as [0.85, 0.99].

5. Conclusion

This paper proposes a long-term smart generation control framework with a unified time-scale to replace the conventional combined generation control framework with multiple time-scales. And then this paper proposes time series generative adversarial network controller for the long-term smart generation control framework of microgrids. After the training process of the proposed time series generative adversarial network controller, the time series generative adversarial network controller can simultaneously obtain high control and optimal objective value under Hainan Power Grid, IEEE 300-bus power system, and IEEE 1951-bus power system. The major features of the proposed time series generative adversarial network controller can be summarized as follows.

1. Compared with the conventional combined generation control framework, the proposed long-term smart generation control framework is a framework with a unified time-scale rather than a framework with multiple time-scales. Consequently, the long-term smart generation control framework can replace a conventional combined "economic dispatch + smart generation control + generation commands dispatch" framework.
2. Since both reinforcement learning and deep neural networks are introduced into a generative adversarial networks, the proposed time series generative adversarial network controller can provide multiple generation commands for multiple smart generation control units. In addition, the time series generative adversarial network can generate numerous sequence simulation data to simulate real-life data.

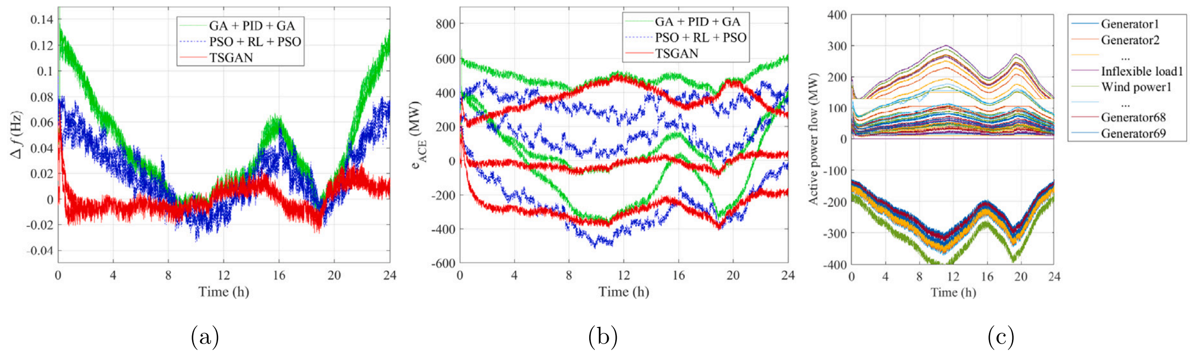


Fig. 11. Frequency deviations, area control errors and active power flows obtained by simulated algorithms in IEEE 300-bus power system: (a) frequency deviation Δf (Hz); (b) area control error e_{ACE} (MW); (c) active power flow (MW).

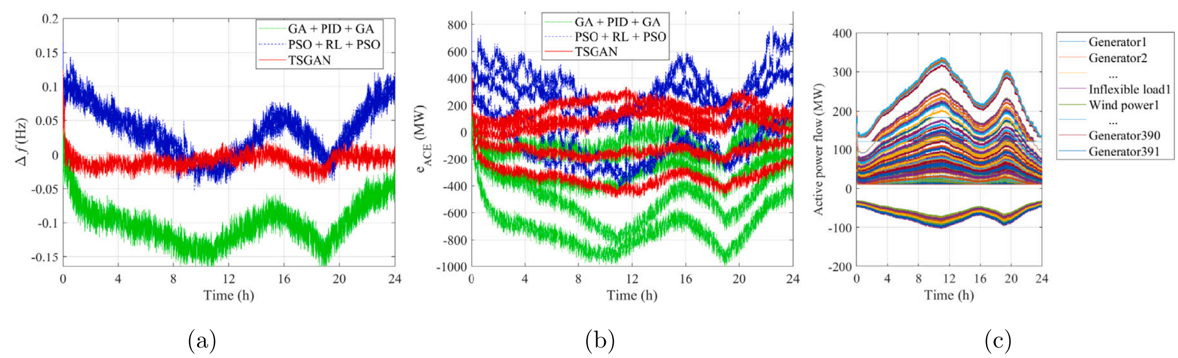


Fig. 12. Frequency deviations, area control errors and active power flows obtained by simulated algorithms in IEEE 1951-bus power system: (a) frequency deviation Δf (Hz); (b) area control error e_{ACE} (MW); (c) active power flow (MW).

3. After the systemic states predicted by the proposed method, the proposed time series generative adversarial network controller can simultaneously obtain higher control performance and smaller economic objective value than the conventional control algorithm and optimization algorithms for the generation control of microgrids. The uncoordinated problems between the control algorithm and optimization algorithms of the generation control problem of microgrids can be solved by the proposed approach.

In the future work, the time series generative adversarial network controller could be applied to coordinated secondary voltage control with a unified time-scale. Besides, a simplified structure of time series generative adversarial network controller could be improved for higher control performance and lesser training time. Furthermore, expandable deep learning and expandable width learning could be introduced into the time series generative adversarial network controller to control a microgrid network with dynamic topology.

Nomenclature

Abbreviations

ACE	Area control error
AGC	Automatic generation control
DGANs	Deep generative adversarial networks
DNNs	Deep neural networks
ED	Economic dispatch
GANs	Generative adversarial networks
GCD	Generation commands dispatch
LTSGC	Long-term smart generation control
MAS	Multi-agent system
SGC	Smart generation control
TSGAN	Time series generative adversarial network
RBMs	Restricted Boltzmann machines
PSO	Particle swarm optimization
PID	Proportional–integral–derivative

CRediT authorship contribution statement

Linfei Yin: Conceptualization, Supervision, Methodology, Writing - review & editing. **Bin Zhang:** Data curation, Software, Validation, Writing - original draft.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.apenergy.2020.116069.

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Appendix. Parameters of Hainan power grid

$P_{\max}$(MW) = {455, 455, 130, 130, 162, 80, 85, 55}
$P_{\min}$(MW) = {120, 120, 20, 20, 25, 20, 25, 10}
α of ED in Eq. (1) = {3.375, 1.125, 1.689, 1.576, 1.17, 1.576, 1.576, 0.674}
β of ED in Eq. (1) = {1800, 600, 897, 837, 624, 837, 837, 362}

γ of ED in Eq. (1) = {56250, 18770, 28170, 26290, 19530, 26290, 26290, 11060}

a of ED in Eq. (1) = {1000, 970, 700, 680, 450, 370, 480, 660}

b of ED in Eq. (1) = {16.19, 17.26, 16.6, 16.5, 19.7, 22.26, 27.74, 25.92}

c of ED in Eq. (1) = {0.00048, 0.00031, 0.002, 0.00211, 0.00398, 0.00712, 0.00079, 0.00413}

References

[1] Karavas CS, Arvanitis KG, Kyriakarakos G, Piromalis DD, Papadakis G. A novel autonomous PV powered desalination system based on a DC microgrid concept incorporating short-term energy storage. Sol Energy 2018;159:947–61.
[2] Lasseter RH. Smart distribution: Coupled microgrids. Proc IEEE 2011;99(6):1074–82.
[3] Hatziargyriou N, Asano H, Iravani R, Marnay C. Microgrids. IEEE Power Energy Mag 2007;5(4):78–94.
[4] Karavas CS, Kyriakarakos G, Arvanitis KG, Papadakis G. A multi-agent decentralized energy management system based on distributed intelligence for the design and control of autonomous polygeneration microgrids. Energy Convers Manage 2015;103:166–79.
[5] Dehnavi G, Ginn HL. Distributed load sharing among converters in an autonomous microgrid including PV and wind power units. IEEE Trans Smart Grid 2019;10(4):4289–98.
[6] Rocabert J, Luna A, Blaabjerg F, Rodríguez P. Control of power converters in AC microgrids. IEEE Trans Power Electron 2012;27(11):4734–49.
[7] Lasseter RH. Microgrids. In: 2002 IEEE power engineering society winter meeting. conference proceedings, vol. 1. 2002, p. 305–8, vol.1.
[8] Lopes JAP, Moreira CL, Madureira AG. Defining control strategies for microgrids islanded operation. IEEE Trans Power Syst 2006;21(2):916–24.
[9] Karavas CS, Arvanitis K, Papadakis G. A game theory approach to multi-agent decentralized energy management of autonomous polygeneration microgrids. Energies 2017;10(11). http://dx.doi.org/10.3390/en10111756.
[10] Xi L, Chen J, Huang Y, Xu Y, Liu L, Zhou Y, et al. Smart generation control based on multi-agent reinforcement learning with the idea of the time tunnel. Energy 2018;153:977–87.
[11] Yan Z, Xu Y. Data-driven load frequency control for stochastic power systems: A deep reinforcement learning method with continuous action search. IEEE Trans Power Syst 2018;34(2):1653–6.
[12] Ni Z, Paul S. A multistage game in smart grid security: A reinforcement learning solution. IEEE Trans Neural Netw Learn Syst 2019;30(9):2684–95.
[13] Patel R, Li C, Meegahapola L, McGrath B, Yu X. Enhancing optimal automatic generation control in a multi-area power system with diverse energy resources. IEEE Trans Power Syst 2019;34(5):3465–75.
[14] Zhang XS, Xu Z, Yu T, Yang B, Wang H. Optimal mileage based AGC dispatch of a GenCo. IEEE Trans Power Syst 2020;1–11. http://dx.doi.org/10.1109/TPWRS.2020.2966509, Early Access.
[15] AL-Musaylh MS, Deo RC, Li Y, Adamowski JF. Two-phase particle swarm optimized-support vector regression hybrid model integrated with improved empirical mode decomposition with adaptive noise for multiple-horizon electricity demand forecasting. Appl Energy 2018;217:422–39.
[16] Chan CM, Bai HL, He DQ. Blade shape optimization of the savonius wind turbine using a genetic algorithm. Appl Energy 2018;213:148–57. http://dx.doi.org/10.1016/j.apenergy.2018.01.029.
[17] Ghasemi-Marzbali A. Multi-area multi-source automatic generation control in deregulated power system. Energy 2020;201:117667.
[18] Huang Q, Huang R, Hao W, Tan J, Fan R, Huang Z. Adaptive power system emergency control using deep reinforcement learning. IEEE Trans Smart Grid 2019;1–12,.
[19] Yin L, Li S, Liu H. Lazy reinforcement learning for real-time generation control of parallel cyber–physical–social energy systems. Eng Appl Artif Intell 2020;88:103380.
[20] Yin L, Yu T, Yang B, Zhang X. Adaptive deep dynamic programming for integrated frequency control of multi-area multi-microgrid systems. Neurocomputing 2019;344:49–60.
[21] Yin L, Gao Q, Zhao L, Wang T. Expandable deep learning for real-time economic generation dispatch and control of three-state energies based future smart grids. Energy 2019;116561.
[22] Yin L, Yu T, Zhang X, Yang B. Relaxed deep learning for real-time economic generation dispatch and control with unified time scale. Energy 2018;149:11–23.
[23] Cheng L, Yu T, Zhang X, Yang B. Parallel cyber-physical-social systems based smart energy robotic dispatcher and knowledge automation: Concepts, architectures, and challenges. IEEE Intell Syst 2018;34(2):54–64.
[24] Jiang CX, Jing ZX, Cui XR, Ji TY, Wu QH. Multiple agents and reinforcement learning for modelling charging loads of electric taxis. Appl Energy 2018;222:158–68.
[25] Mukhlish F, Page J, Bain M. Evolutionary-learning framework: improving automatic swarm robotics design. Int J Intell Unmanned Syst 2018;6(4):197–215.
[26] Ding D, Ding Z, Wei G, Han F. An improved reinforcement learning algorithm based on knowledge transfer and applications in autonomous vehicles. Neurocomputing 2019;361:243–55.
[27] Han X, He H, Wu J, Peng J, Li Y. Energy management based on reinforcement learning with double deep Q-learning for a hybrid electric tracked vehicle. Appl Energy 2019;254:113708.
[28] Zhang X, Tan T, Yang B, Wang J, Li S, He T, et al. Greedy search based data-driven algorithm of centralized thermoelectric generation system under non-uniform temperature distribution. Appl Energy 2020;260:114232.
[29] Ezhilsabareesh K, Suchithra R, Samad A. Performance enhancement of an impulse turbine for OWC using grouped grey wolf optimizer based controller. Ocean Eng 2019;190:106425.
[30] Wei H, Hongxuan Z, Yu D, Yiting W, Ling D, Ming X. Short-term optimal operation of hydro-wind-solar hybrid system with improved generative adversarial networks. Appl Energy 2019;250:389–403.
[31] Yin L, Gao Q, Zhao L, Zhang B, Wang T, Li S, et al. A review of machine learning for new generation smart dispatch in power systems. Eng Appl Artif Intell 2020;88:103372.
[32] Stone JV. Climbing mount AI. Nat Mach Intell 2019;1(1):7.
[33] Liu X, Weijer Jvd, Bagdanov AD. Exploiting unlabeled data in CNNs by self-supervised learning to rank. IEEE Trans Pattern Anal Mach Intell 2019;41(8):1862–78.
[34] Ma D, Tang P, Zhao L. Siftinggan: Generating and sifting labeled samples to improve the remote sensing image scene classification baseline in vitro. IEEE Geosci Remote Sens Lett 2019;16(7):1046–50.
[35] Creswell A, Bharath AA. Inverting the generator of a generative adversarial network. IEEE Trans Neural Netw Learn Syst 2019;30(7):1967–74.
[36] Yu L, Zhang W, Wang J, Yu Y. Seqgan: Sequence generative adversarial nets with policy gradient. 2016, CoRR abs/1609.05473. arXiv:1609.05473.
[37] Cui B, Sun XA. A new voltage stability-constrained optimal power-flow model: Sufficient condition, SOCP representation, and relaxation. IEEE Trans Power Syst 2018;33(5):5092–102.