An Interval Voltage Control Method Using Adaptive Genetic Algorithm

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***Abstract*—This paper proposes the use of interval values to model the power output of renewable energy resources, and accordingly develops an interval voltage control model. The proposed model can safeguard the security of power grids by ensuring that the voltages reside within established limits. An adaptive genetic algorithm is employed to solve the proposed model, where a newly developed interval power flow calculation is used to solve the interval power flow equations, and penalty functions are applied to express inequality constraints. The proposed method is introduced in detail, and simulation results are presented to demonstrate its performance in comparison with a previously proposed interval voltage control method. The proposed approach provides robust convergence, obtains lower system power losses, and substantially reduces the computation time.**

***Index Terms*—Renewable energy, interval, voltage control, adaptive genetic algorithm.**

I. INTRODUCTION

Renewable energy resources mainly include hydroelectric power, wind power, and solar power. These power sources are mainly utilized by power systems to provide electric power generation for consumers. The wind and solar power resources are very difficult to control because they depend on wind speed and sunshine intensity, which vary irregularly, and are very difficult to predict [1]. Therefore, the output power of wind and solar energy resources represents uncertain data in power systems. This uncertainty has a great influence on the operating security of power grids, particularly the voltage security. A general approach to voltage security is to consider the uncertainty in a voltage control model.

The voltage control research conducted in this paper mainly focuses on reactive power optimization (RPO). RPO is applied to reduce the operating cost (real power losses) of the power grid or improve the voltage quality under a series of security constraints and operating constraints [2].

Deterministic RPO problems have been solved adequately by both classical [3]-[5] and artificial intelligence algorithms [6]-[8]. However, the incorporation of renewable energy resources introduces uncertainties in the input data that must be accommodated by the corresponding RPO model. This is denoted as an uncertain RPO (URPO) model. The solution of URPO problems has mainly employed three types of approaches, i.e., stochastic programming (SP) [9], robust programming (RP) [10], [11], and interval optimization (IP) [12]. The SP method regards uncertain inputs as random variables with a specific distribution, and the URPO is thus expressed as a SP problem [13], whose objectives and constraints are set at specific confidence levels. To solve an SP model, artificial intelligence algorithms incorporating the Monte Carlo technique have been employed. However, Monte Carlo processes require a considerable amount of time, and the voltage control strategies obtained by the SP method cannot ensure the fulfillment of security constraints, indicating that some variables may go beyond the limits of their constraints. As for the RP method, it expresses uncertain input data as interval values with upper and lower bounds. The RP model is therefore established by considering the boundaries of the identified constraints. It has been proven that control strategies acquired by the RP method can ensure that variables remain within their bounded limits [14]. However, it should be noted that the RP method is only applicable to convex problems (including linear programming problems). Therefore, nonlinear power flow equations must first be linearized or made convex before being employed in the RP method [11]. As a result, it is possible for the control strategy obtained by the RP method to fail to fulfill the original security constraints adopted prior to linearization or convexification. The IP method was therefore proposed to ensure the fulfillment of security constraints. This method also regards uncertain input data as interval variables, and builds an interval reactive power optimization (IRPO) model. To solve this model, the IP method employs a genetic algorithm (GA), where an interval power flow calculation (IPFC) is used to obtain conservative ranges of the state variables (including the voltages and reactive power generation levels). These conservative ranges are employed for evaluating the security constraints, which ensures that the security constraints are satisfied by the control strategy obtained by the IP method. Although the IRPO model has been solved using a GA in previous work [12], this approach has some problems. These problems mainly include two aspects. 1) The results obtained by the IPFC method are too conservative, and thus result in poor power system performance as well as difficulty in acquiring feasible solutions. 2) The convergence efficiency of a standard GA is too low, which makes it time-consuming for solving the IRPO model. To overcome these two problems, this paper proposes an adaptive GA (AGA) to solve the IRPO model. To address problem 1), the proposed AGA employs a

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better IPFC method for obtaining more accurate interval variable ranges for the IRPO model. As for problem 2), the AGA selects the probability parameters of the crossover and mutation procedures according to an adaptive strategy [15]. Meanwhile, a penalty function is employed as an efficient means of handling constraints, which simplifies the process of assembling the initial population of feasible solutions. This modification saves considerable computation time. Accordingly, we conduct the following work.

- The most accurate IPFC method is applied to evaluate the ranges of the variables employed in the IRPO model. In this manner, the feasible region of the IRPO model can be expanded, and thus reduce the optimized value of the objective function, i.e., reduce the real power losses.
- The AGA is employed to solve the IRPO model. The AGA can ensure that the voltages reside within their security limits as well as maintain a low level of real power losses.
- A penalty function is employed to replace the direct consideration of constraints. This improves the efficiency for solving the IRPO model.

The remainder of this paper is arranged as follows. The formulation of the IRPO model is introduced in Section II. The AGA procedure employed for solving the IRPO model is presented in Section III. Simulation results are presented in Section IV. The conclusions and contributions are given in Section V.

II. Problem Formulation

A. RPO model

The RPO model includes an objective function, power flow equations, and constraints such as voltage limits, reactive power generation limits, transformer ratio limits, and reactive power compensator output limits [12]. Accordingly, the RPO model can be expressed as a minimization of the following objective function representing the real power losses:

$$\min P_{\mathrm{loss}} = \sum_{i\in \mathrm{S}}\sum_{j\in \mathrm{S}} V_i V_j G_{ij}\cos\theta_{ij}\ , \tag{1}$$

where i and j are within the set of system buses S, V_i is the load bus voltage, G_{ij} is the real part of the admittance, and $\theta_{ij}=\theta_i-\theta_j$ is the bus angle. Equation (1) is subject to the following power-flow relationships and constraints.

$$\begin{cases} P_{\mathrm{G}i}-P_{\mathrm{L}i}-P_i=0,\ i\in \mathrm{S_G} \\ Q_{\mathrm{G}i}-Q_{\mathrm{L}i}-Q_i=0,\ i\in \mathrm{S'_G} \end{cases} \tag{2}$$

$$\begin{cases} \quad -P_{\mathrm{L}i}-P_i=0,\ i\in \mathrm{S_L} \\ Q_{\mathrm{C}i}-Q_{\mathrm{L}i}-Q_i=0,\ i\in \mathrm{S_L} \end{cases} \tag{3}$$

$$Q_{\mathrm{G}i}^{\min}\le Q_{\mathrm{G}i}\le Q_{\mathrm{G}i}^{\max},\ i\in \mathrm{S_G} \tag{4}$$

$$Q_{\mathrm{C}i}^{\min}\le Q_{\mathrm{C}i}\le Q_{\mathrm{C}i}^{\max},\ i\in \mathrm{S_C} \tag{5}$$

$$V_i^{\min}\le V_i\le V_i^{\max},\ i\in \mathrm{S_G}\bigcup \mathrm{S_L} \tag{6}$$

$$T_l^{\min}\le T_l\le T_l^{\min},\ l\in \mathrm{S_T} \tag{7}$$

Here, superscripts max and min represent maximum and minimum limit values, and the total nodal active and reactive power are respectively given as

$$P_i=P_i(\boldsymbol{V},\boldsymbol{\theta},\boldsymbol{T})=V_i\sum_{j\in \mathrm{S}}V_j(G_{ij}\cos\theta_{ij}+B_{ij}\sin\theta_{ij})\ , \tag{8}$$

$$Q_i=Q_i(\boldsymbol{V},\boldsymbol{\theta},\boldsymbol{T})=V_i\sum_{j\in \mathrm{S}}V_j(G_{ij}\sin\theta_{ij}-B_{ij}\cos\theta_{ij})\ , \tag{9}$$

where B_{ij} is the imaginary part of the admittance. The terms $\mathrm{S_G}$, $\mathrm{S'_G}$, $\mathrm{S_L}$, $\mathrm{S_C}$, and $\mathrm{S_T}$ represent sets of generator buses, generator buses including the slack bus, load buses, reactive power compensators, and transformers, respectively. $P_{\mathrm{G}i}$ and $Q_{\mathrm{G}i}$ represent the active and reactive power generation, respectively, $P_{\mathrm{L}i}$ and $Q_{\mathrm{L}i}$ are the active and reactive power load demands, respectively, and $Q_{\mathrm{C}i}$ is the reactive power compensator output (e.g., a capacitor).

B. RPO model considering renewable energy resources

When the RPO model incorporates intermittent energy resources, the input data $P_{\mathrm{G}i}$, $P_{\mathrm{L}i}$, and $Q_{\mathrm{L}i}$ are treated as uncertain variables [16], [17]. An effective approach to deal with uncertainty is to express the uncertainties as intervals [12], i.e., $P_{\mathrm{G}i}$, $P_{\mathrm{L}i}$, and $Q_{\mathrm{L}i}$ are represented as intervals $[P_{\mathrm{G}i}^{\mathrm{SL}},P_{\mathrm{G}i}^{\mathrm{SU}}]$ (for $i\in \mathrm{S_G}$) , $[P_{\mathrm{L}i}^{\mathrm{SL}},P_{\mathrm{L}i}^{\mathrm{SU}}]$(for $i\in \mathrm{S_L}$) , and $[Q_{\mathrm{L}i}^{\mathrm{SL}},Q_{\mathrm{L}i}^{\mathrm{SU}}]$(for $i\in \mathrm{S_L}$) , respectively. Therefore, the RPO model incorporating renewable energy resources can be expressed as

$$\min f(\boldsymbol{X},\boldsymbol{u})\,. \tag{10}$$

Here $f(\boldsymbol{X},\boldsymbol{u})$ represents the real power losses expressed in (1), where $\boldsymbol{X}$ is a vector of state variables, including $\theta_i(i\in \mathrm{S_G}\bigcup \mathrm{S_L})$, $V_i\ (i\in \mathrm{S_L})$, and $Q_{\mathrm{G}i}(i\in \mathrm{S_G})$, and $\boldsymbol{u}$ is a vector of control variables, which consists of generator bus voltages $V_i\ (i\in \mathrm{S_G})$, $Q_{\mathrm{C}i}(i\in \mathrm{S_C})$, and $T_l(\ l\in \mathrm{S_T})$. The power flow equations and constraints are given as follows.

$$\begin{cases} P_{\mathrm{L}i}+P_i=[P_{\mathrm{G}i}^{\mathrm{SL}},P_{\mathrm{G}i}^{\mathrm{SU}}],\ i\in \mathrm{S_G} \\ Q_{\mathrm{G}i}-Q_{\mathrm{L}i}-Q_i=0,\ i\in \mathrm{S'_G} \end{cases} \tag{11}$$

$$\begin{cases} \quad -P_i=[P_{\mathrm{L}i}^{\mathrm{SL}},P_{\mathrm{L}i}^{\mathrm{SU}}],\ i\in \mathrm{S_L} \\ Q_{\mathrm{C}i}-Q_i=[Q_{\mathrm{L}i}^{\mathrm{SL}},Q_{\mathrm{L}i}^{\mathrm{SU}}],\ i\in \mathrm{S_L} \end{cases} \tag{12}$$

$$\boldsymbol{g}^{\min}\le \boldsymbol{g}(\boldsymbol{X},\boldsymbol{u})\le \boldsymbol{g}^{\max} \tag{13}$$

Equation (13) represents the inequality constraints (4)–(7), and P_i and Q_i are again calculated by (8) and (9), respectively. Because this paper mainly focuses on developing control strategies to ensure the security of a power system, $\min f(\boldsymbol{X},\boldsymbol{u})$ is simplified as $\min \mathrm{midpoint}\{f(\boldsymbol{X},\boldsymbol{u})\}$, i.e., minimizing the midpoint of the real power losses. The physical significance of the IRPO model is that it minimizes the average level of the real power losses by coordinating the values of $\boldsymbol{u}$ while ensuring that the values of $\boldsymbol{X}$ reside within the security limits.

III. SOLUTION OF THE IRPO MODEL

As previously discussed, the present work employs an improved IPFC method for obtaining more accurate interval value ranges for the IRPO model [18], and an AGA that selects the probability parameters of the crossover and mutation procedures according to an adaptive strategy is proposed for providing a more robust solution to the IRPO model. Finally, a penalty function is employed as a computationally efficient means of considering constraints. These modifications are discussed in detail, as follows.

A. An improved IPFC for addressing uncertain input data

A load flow problem employing input data given as intervals is represented by an interval power flow (IPF) model, which is herein expressed by (11) and (12). To solve IPF models, an improved IPFC method has been proposed [18] that computes the interval variable ranges of an IPF model with better accuracy. This method is mainly based on the extreme value theorem, and employs two types of optimization models, i.e., maximum and minimum models, to obtain the interval variable ranges of the IPF model directly. These two models can be expressed as follows.

$$\min x_i \quad (\text{or} \max x_i)$$
$$s.t. \begin{cases} \boldsymbol{h}(\boldsymbol{x}) = \boldsymbol{\xi} \\ \boldsymbol{h}^{\mathrm{L}} \le \boldsymbol{\xi} \le \boldsymbol{h}^{\mathrm{U}} \end{cases} \tag{14}$$

Here, x_i represents $V_i\ (i \in \mathrm{S_L})$, $\theta_i\ (i \in \mathrm{S_G} \cup \mathrm{S_L})$, and $Q_{\mathrm{G}i}\ (i \in \mathrm{S_G})$, and $\boldsymbol{h}(\boldsymbol{x}) = \boldsymbol{\xi}$ represents the power flow balance equations (11) and (12), where $\boldsymbol{\xi}$ are variables in the intervals $[\boldsymbol{h}^{\mathrm{L}}, \boldsymbol{h}^{\mathrm{U}}]$ based on lower and upper bounds denoted by the superscripts L and U, respectively. The models given by (14) are nonlinear programs, which can be efficiently solved using the IPM [2]. Relative to standard IPFC methods, this IPFC method has been demonstrated to acquire the most accurate ranges of an IPF model. This method is employed by the AGA to solve the IRPO model.

B. AGA for solving the IRPO model

The procedures of the proposed AGA are similar to those published previously [12], and they can be described using the following steps.

step 1) Input data and set the parameters of the AGA. The input data mainly consist of the varying intervals of the load demands, the active power generation of renewable resources, and the parameters of the network. AGA parameters include $\mathrm{N_P}$: the size of the solution population; $\mathrm{P_m^0}$: initial probability of mutation; $\mathrm{P_c^0}$: initial probability of crossover; β : penalty factor; M : maximum iteration.

step 2) Generate the initial solution population. The solution population is composed of control variables, denoted as $(\boldsymbol{u}^1, \boldsymbol{u}^2, \ldots, \boldsymbol{u}^{\mathrm{N_P}})$. The improved IPFC method is employed here to obtain the ranges of the state variables and objective function f_{M} . Set iteration $k = 0$.

step 3) Perform crossover. This process involves the transmission of information between individual solutions. First of all, individual solutions are selected from the current population for participating in the crossover process according to a probability $\mathrm{P_c}^{i,k}$ (i.e., the crossover probability of the i^{th} individual at the k^{th} iteration). Second, all the selected individuals are paired randomly (one individual is abandoned if the number of selected individuals is odd). Finally, conduct crossover for each pair. For instance, for pair ($\boldsymbol{u}^i$, $\boldsymbol{u}^j$), new individual solutions are produced by the operations

$$\boldsymbol{u}^{i*} = c\boldsymbol{u}^i + (1-c)\boldsymbol{u}^j \tag{15}$$

and

$$\boldsymbol{u}^{j*} = (1-c)\boldsymbol{u}^i + c\boldsymbol{u}^j , \tag{16}$$

where c is a random value in (0,1).

step 4) Conduct mutation. This step is employed to expand the search scope of the algorithm. Individuals are first selected from the current population according to a probability $\mathrm{P_m}^{i,k}$ (i.e., the mutation probability of the i^{th} individual at the k^{th} iteration), and, for each selected individual $\boldsymbol{u}^i$, a new individual is generated by the operation

$$\boldsymbol{u}^{i0} = \boldsymbol{u}^i + D\vec{\boldsymbol{d}} , \tag{17}$$

where $\vec{\boldsymbol{d}}$ is a random direction, and each dimension is limited in $(-1,1)$, and D is an amplification factor. Here, the IPFC method is employed to obtain the ranges of the state variables.

step 5) Sort the populations according to the values of their objective functions. We set

$$f = 1/(f_{\mathrm{M}} + \beta P(x)) \tag{18}$$

as the fitness function, which is the basis for sorting the current population. $P(x)$ is the penalty function. Every $\boldsymbol{u}$ is sorted in ascending order according to its corresponding value of f .

step 6) Select individuals from the present population to create a next generation population using the Roulette method. By constructing the evaluation function

$$\begin{cases} q(i) = q(i-1) + f^i, 1 \le i \le \mathrm{N_P} + 1 \\ q(0) = 0 \end{cases} \tag{19}$$

and adopting the Roulette method to filter the current population. Here, f^i is the fitness function of the i^{th} individual. A random value r_q is generated in the range of (0,1). If $r_q q(\mathrm{N_P}) \in [q(i-1), q(i)]$, then $\boldsymbol{u}^i$ is selected as a member of the new population. A new population is produced by repeating this operation $\mathrm{N_P}$ times.

step 7) Stop and record results if $k > \mathrm{M}$; otherwise, continue conducting step 3) to step 6).

The calculation of probability parameters $P_c^{i,k}$ in step 3) and $P_m^{i,k}$ in step 4) can be found in [15].

After conducting M iterations, we obtain an optimal solution $\boldsymbol{u}^*$ as well as its corresponding real power losses at the midpoint f_M^*.

IV. Simulation Results

To validate the effectiveness of the proposed AGA optimization approach discussed in the previous section, an optimum voltage control strategy was obtained for a modified IEEE30 test system. The results obtained using the proposed AGA are compared with those acquired using the basic GA approach proposed in a previous work [12]. All parameters are valued according to the per unit (p.u.) system of analysis. The voltage limits of power generators are set as [0.9, 1.1] while the load bus voltages are constrained to [0.95, 1.05]. The transformer ratios are all limited in [0.9, 1.1], with uniform switched steps equal to 0.05. The parameters of the capacitors are listed in Table. I. More detailed information regarding this system can be obtained elsewhere [19]. The active power generation ranges of the renewable resource power generators and active and reactive power load demand are assumed to be ±30% of the original data. The parameters of the AGA are listed in Table. II. We note that the AGA employs larger initial probabilities for crossover and mutation than those parameters of the GA as also discussed in [15]. All the simulation tests were conducted using MATLAB R2016b on a 3.2-GHz CPU. The simulation results are presented relative to three aspects, i.e., convergence and optimality, effectiveness of constraints, and CPU time.

A. Convergence and optimality

The midpoint of the real power losses obtained using the AGA and GA methods are presented in Fig. 1. First, we note that the convergence behavior of the AGA is much more robust than that of the GA, where the value of the objective function steadily decreases with increasing iterations. This is because, with increasing iterations, the AGA is more likely to select better individuals for forming the next generation according to its adaptive probability parameters for crossover and mutation [15]. Second, we note that the midpoint level of real power losses obtained by AGA is much less than that acquired by the GA. This is expected because the feasible region in the AGA is much wider than that in the GA due to the more accurate IPFC method employed by the AGA. The optimal voltage control strategy obtained by the AGA is

$$[T_{6-9}, T_{6-10}, T_{4-12}, T_{28-27}, Q_{C10}, Q_{C24}, V_{G2}, V_{G5}, V_{G8}, V_{G11}, V_{G13}] = [1.0, 1.0, 1.0, 1.0, 0.3, 0.06, 1.034, 0.972, 1.067, 0.992, 0.956].$$

TABLE I. Parameters of Capacitors in the IEEE30 Test System

Bus no	Lower Bound	Upper Bound	Switch Step
10	0	0.5	0.1
24	0	0.1	0.02

TABLE II. Parameters of the AGA and GA [12]

Algorithm	N_p	M	β	P_m^0	P_c^0
AGA	30	80	10	0.6	0.7
GA	30	80		0.2	0.3

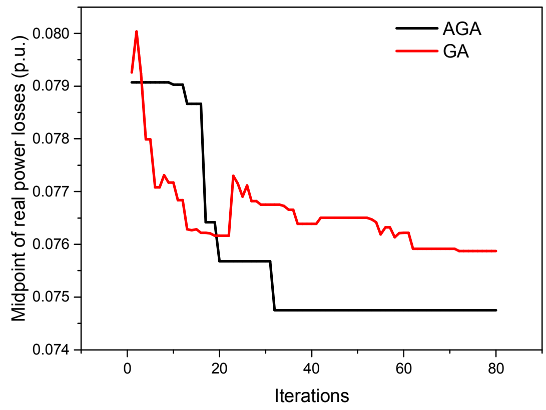

Fig. 1. Midpoint of the real power losses at each iteration obtained by the AGA and GA [12]

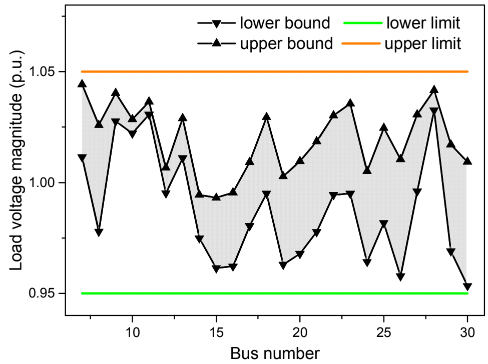

Fig. 2. Interval results of the load bus voltages obtained by the AGA

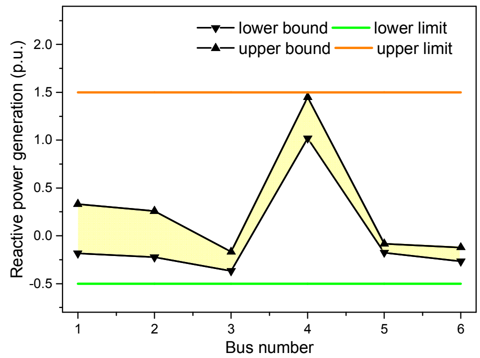

Fig. 3. Interval results of the reactive power generation of generation buses obtained by the AGA

B. Effectiveness of constraints

To demonstrate the effectiveness of the AGA for adhering to the established constraints, the obtained ranges of load bus voltages and the reactive power generation of generator buses are given in Fig. 2 and Fig. 3, respectively. We note that all load bus voltages and reactive power generation values are within the corresponding limit constraints. This is because all the constraints are satisfied using the conservative ranges obtained by the IPFC method, which actively ensures that the interval variables are constrained within their respective limits. These results indicate that the proposed AGA can ensure the operating security of the power system when incorporating renewable energy resources with uncertain power generation outputs.

C. CPU time

The AGA requires about 60 s to determine an optimal voltage control strategy for the test IEEE30 system, while the previously proposed GA requires about 900 s. This obviously represents a very substantial reduction in the required computation time.

V. Conclusion

This paper aims to obtain voltage control strategies for actively ensuring that the voltages (or the reactive power generation) reside within established limits by regarding the uncertain input data associated with renewable energy resource power generation and load demands as interval variables, and the IRPO model is built accordingly. A more sophisticated GA that provides more robust convergence has been proposed to solve the IRPO model. In addition, the proposed AGA obtains lower system power losses by employing a more accurate IPFC method for computing the intervals of state variables, and also applies penalty functions to express the inequality constraints, which substantially reduces the computation time. The results of testing IEEE30 system showed that the AGA could acquire a voltage control strategy that ensured the operating security of the power system, and that the AGA performed better than a standard GA in terms of robust convergence, optimality of the obtained control strategy, and the required CPU time.

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