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Special Focus on Pigeon-Inspired Optimization

A novel binary/real-valued pigeon-inspired optimization for economic/environment unit commitment with renewables and plug-in vehicles

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Dear editor,

Among multiple levels of power and energy scheduling, day-ahead unit commitment (UC) has long been a challenging task for power system operators owing to the strong constrained, mixed-integer, and high-dimensional characteristics. The objective of UC is to minimize the fossil fuel cost in thermal power generation by determining the on–off status and power generation output while maintaining physical constraints, such as the demand balance and capacity limits [1]. Over the past few decades, numerous studies have focused on the development of alternative and efficient computational tools for solving the UC problem. Given the complicated formulation, conventional methods perform well for solving normal scale problems [2, 3]; however endures dimensional curse for large-scale tasks, whereas pure real-valued methods often display low efficiency and produce unstable results. Binary methods combined with lambda iteration methods have been shown to provide a trade-off between the computational load and accuracy. However, new participants such as renewable energy generation (REG) and plug-in electric vehicles (PEVs) would further address more intractable factors for the original difficult UC problem.

Problem formulation. An economic and environmental UC that considers deterministic REG scenarios and flexible integration of PEVs (i.e., EEUCRP) is proposed, where the decision variables include the binary status and real-valued output of power generations, as well as the PEVs power flow for a 24-h day-ahead time horizon. To tackle the mixed-integer high-dimension problem, a novel binary/real-valued hybrid coding pigeon-inspired optimization (BRPIO) method is proposed, and the multi-objective problem is converted to a single objective problem using weighting factors. Analysis of the results of the methods used for optimal solutions of both economic and emission minimization are also addressed.

The proposed EEUCRP problem inherits the key components of the original UC [1], whereas the emission is modelled in the objective functions; in addition, new constraints are established with REGs and PEVs that consider the power demand and spinning reserve limit. The objective function

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is modeled from the economic and environmental factors; the economic cost C_{eco} includes fuel and start-up costs, and the emission C_{emi} is modeled with a quadratic formulation.

The fuel cost is the economic cost incurred from the fossil fuel consumption associated with thermal generation, which is commonly modeled using a quadratic equation,

$$F_{j,t}^{\mathrm{fuel}}(P_{j,t}) = a_j + b_j P_{j,t} + c_j P_{j,t}^2, \tag{1}$$

where $F_{j,t}^{\mathrm{fuel}}$ and $P_{j,t}$ denote the cost of fuel and power output of the j-th unit in the t time interval. a_j, b_j, and c_j denote the cost coefficients.

Extra cost $\mathrm{SU}_{j,t}$ for the restart of thermal power units includes the cold start cost $\mathrm{SU}_{C,j}$ and the hot start cost $\mathrm{SU}_{H,j}$. Once the off-line duration $\mathrm{TOFF}_{j,t}$ of a unit passes the cold period $T_{\mathrm{cold},j}$, the higher cost $\mathrm{SU}_{C,j}$ must be adopted.

$$\mathrm{SU}_{j,t} = \begin{cases} \mathrm{SU}_{H,j}, \text{ if } \mathrm{MDT}_j \leqslant \mathrm{TOFF}_{j,t} \\ \qquad\qquad \leqslant \mathrm{MDT}_j + T_{\mathrm{cold},j}; \\ \mathrm{SU}_{C,j}, \text{ if } \mathrm{TOFF}_{j,t} > \mathrm{MDT}_j + T_{\mathrm{cold},j}. \end{cases} \tag{2}$$

MDT_j and MUT_j are minimum down and up times, respectively. To accumulate the total economic cost, the total time T (24-h day-ahead UC problem) is accumulated along the time horizon.

$$C_{\mathrm{eco}} = \sum_{t=1}^{T}\sum_{j=1}^{n}\big[F_{j,t}^{\mathrm{fuel}}(P_{j,t})u_{j,t} + \mathrm{SU}_{j,t}(1-u_{j,t-1})u_{j,t}\big], \tag{3}$$

where C_{eco} denotes the total economic cost, and $u_{j,t}$ is the binary decision variable of the given units.

Emission costs are the equivalent weights of air pollutant emissions, which are modeled as quadratic formulation [4].

$$F_{j,t}^{\mathrm{emi}}(P_{j,t}) = \alpha_j + \beta_j P_{j,t} + \gamma_j P_{j,t}^2, \tag{4}$$

where $F_{j,t}^{\mathrm{emi}}$ is the emission cost, whereas α_j, β_j, and γ_j denote the emission cost coefficients. The total emission cost C_{emi} is expressed as follows:

$$C_{\mathrm{emi}} = \sum_{t=1}^{T}\sum_{j=1}^{n}[F_{j,t}^{\mathrm{emi}}(P_{j,t})u_{j,t}], \tag{5}$$

where the all-time cost is accumulated in the C_{emi} considering the on/off line status. In summary, the total cost C_{total} includes both economic and emission factors and is expressed as follows:

$$\min\ C_{\mathrm{total}} = \omega \cdot C_{\mathrm{eco}} + (1-\omega)\cdot C_{\mathrm{emi}}, \tag{6}$$

where the two objectives C_{eco} and C_{emi} are merged using a weighting factor ω, and converted into a single objective optimization.

In the new EEUCRP equation, the constraints include the power generation, power demand, spinning reserve, minimum up/down, and PEV power limits. Based on [5], the REG and PEV powers are embedded into the original UC problem constraints.

Binary pigeon-inspired optimization. Pigeon-inspired optimization is a recent proposed bio-inspired optimization method proposed by Duan and Qiao [6] that mimics the behavior of the pigeon in route navigation by adopting two phases: a map and compass phase and a landmark phase. The method has been adopted for solving various engineering problems such as air robot path planning [6] and neural network optimization [7]. A binary PIO method is proposed and hybridized with real-valued PIO to solve the EEUCRP problem in this study. Binary PIO comprises two phases: a binary landmark phase and a binary map and compass phase, and the velocity is updated by the two binary phases which determines the following operators: (7) and (10). In the binary map and compass phase, velocity updating remains identical to that used in the case of the real-valued PIO, and the algorithm binary decision variables are determined using the probability operators (11).

$$V_{bi}(t) = V_{bi}(t-1)\cdot \mathrm{e}^{-R_b t} + \mathrm{rand}\cdot(X_{bg} - X_{bi}(t-1)), \tag{7}$$

where the X_{bg} and $X_{bi}(t-1)$ represent all binary decisions. In the binary landmark phase, the operators (8) and (9) remain the same, and the velocity update is determined using (10).

$$Np_b(t) = \mathrm{ceil}\left(\frac{Np_b(t-1)}{2}\right), \tag{8}$$

$$X_{bc}(t) = \frac{\Sigma_i(X_{bi}(t)\cdot \mathrm{fitness}(X_{bi}(t)))}{Np_b(t)\Sigma_i \mathrm{fitness}(X_i(t))}, \tag{9}$$

$$V_{bi}(t) = V_{bi}(t-1) + \mathrm{rand}\cdot(\mathrm{round}(X_{bc}(t)) - X_{bi}(t-1)), \tag{10}$$

where the new $X_{bc}(t)$ is handled by a round operator to obtain a binary variable. In both phases, the binary decision variables are determined by the probability, which is calculated using a V-shape transfer function, as shown in (11).

$$\Pr(V_i(t)) = |\tanh(V_{bi}(t))|, \tag{11}$$

$$u_{ij} = \begin{cases} 1-u_{ij}, & \text{if rand} < \Pr(V_{bij}(t)), \\ u_{ij}, & \text{otherwise}. \end{cases} \tag{12}$$

Notably, all variables have an added subscript letter b to distinguish the real-valued PIO. The real-valued and binary PIO work in parallel to solve the mixed-integer EEUCRP problem, and

Table 1 Numerical results for EEUCRP considering G2V/V2G mode

Case	Thermal spinning reserve scenarios ($/day)								
	A-BT	A-WT	A-MN	C-BT	C-WT	C-MN	E-BT	E-WT	E-MN
Case 2-1: 5% reserve	–	–	–	541318	542650	541847	41569	42219	41943
Case 2-2: 10% reserve	561821	566281	564050	545989	547632	546826	41839	42953	42330

the holistic method is named as BRPIO for convenience.

Case study. In the case study, REG capacities of 25.5 MW and 40 MW were considered [8]. The number of available PEVs is 50000 and their average daily traveling distance is 32.88 miles, which requires a total power of 411 MW. Accordingly, the discharging and charging boundaries are calculated as 50000×15 KWh$\times$SOC $50\%\times20\%\times85\%/1$ h $=$ 63.75 MW. The BRPIO algorithm is conducted in 10 independent runs and the number of particles is set as 20. The maximum iteration number is 100, and the map and compass factors for the BRPIO are set as 0.2 and 0.02, respectively, for real-valued R and binary optimization R_b. To eliminate randomness, 30 independent runs are adopted in the algorithm test. The weighting factor ω in (6) is set as 0.9. In addition, we adopt the V2G and G2V mode for PEVs, which allow the bidirectional power flow from/to the grid. The GA-LR method proposed in [9] is employed to compare the results.

Table 1 shows both economic costs and emissions for the scenarios under two different spinning reserve rates, where BT, WT, and MN denote best, worst, and mean values, respectively. Moreover, A- represents the GA-LR results, whereas C- and E- denote the BRPIO for economic and environmental cost results. Note that the proposed BRPIO successfully obtains results that significantly outperform the previous study shown in A- and C- series. E- results denote the obtained environmental emission results, demonstrating the effectiveness of the proposed BRPIO method.

Conclusion. In this study, economic and environmental UC was modeled with the renewable energy and plug-in electric vehicles, formulating a complex high-dimensional mixed-integer problem. A novel binary/real-valued pigeon-inspired optimization method was proposed, which combined the binary and real-valued methods to solve the problem through a parallel approach. The results have validated the effectiveness of the proposed BRPIO method, which could significantly reduce the economic and emission costs for the UC considering complex items such as renewable generation and PEVs. The proposed algorithm also has significant potential in the area of solving more discrete and mixed-integer engineering problems.

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