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Multi-objective biogeography-based optimization for dynamic economic emission load dispatch considering plug-in electric vehicles charging

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A B S T R A C T

The climate change is addressing unprecedented pressures on conventional power system regarding the significant fossil fuel consumptions and carbon emissions, which largely challenges the conventional power system operation. This paper proposes a novel dynamic non-dominated sorting multi-objective biogeography-based optimization (Dy-NSBBO) to solve multi-objective dynamic economic emission load dispatch considering the mass integration of plug-in electric vehicles (PEVs), namely MO-DEELDP problem. First, a real-world economic emission load dispatch considering PEVs charging is first formulated as a constrained dynamic multi-objective optimization problem. Then a new multi-objective BBO is proposed adopting the non-dominated solution sorting technique, change detection and memory-based selection strategies in the multi-objective BBO method to strengthen the dynamic optimization performance. The proposed Dy-NSBBO is applied to solve three different dynamic economic emission load dispatch cases integrating four plug-in electric vehicle charging scenarios respectively. Comprehensive analysis shows that the novel algorithm is promising to bring considerable economic and environmental benefits to the power system operators and provides competitive charging strategies for policy makers and PEVs aggregators.

1. Introduction

Economic emission load dispatch (EELD) problem is one of fundamental issues of power system operation. The objective of EELD is to simultaneously achieve the optimal generation cost and the least emission of power systems while satisfying equality and inequality constraints encompassing power balance, generator capacity, ramping rate constraints and etc. In other words, EELD is a multi-objective optimization problem that determines the optimal power production of power systems by minimizing the generation cost and emission cost [2,14].

Several classical optimization methods, such as gradient-based method and linear programming, have been applied to solve different EELD problems [15]. However, these methods are lack of feasibility and accuracy due to non-convex and nonlinear characteristics of the objective functions and constraints. In the recent decade, meta-heuristic algorithms, such as genetic algorithms (GAs) [5], harmony search algorithm (HSA) [16], gravitational search algorithm (GSA) [24], teaching-learning based optimization (TLBO) [26], biogeography-based optimization (BBO) [18], artificial bee colony (ABC) [19] and flower pollination algorithm (FPA) [1] have been used to solve EELD problems. However, very few concerns have been addressed on new participants of power system such as stochastic renewable energy generations and electric vehicles, which significantly perplex the load dispatch tasks.

Some new attempts have been made to tackle with EELD problems integrated with new participants. In ref. [10], the EELD problem of power system was combined with solar photo voltaic generation solved by particle swarm optimization (PSO). In ref. [11], the authors used stochastic multi-objective optimization for EELD with uncertain wind power and distributed loads. In ref. [4], a

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dynamic EELD problem considering load and wind power uncertainties was optimized by an efficient scenario-based and fuzzy self-adaptive learning particle swarm optimization approach.

Modern plug-in electric vehicles (PEVs) are potentially flexible load demand and promising to replace the fossil fuel powered vehicles due to less exhaust gas emission ([29,27]). On the other hand, the remarkable charging load required from PEVs to maintain the daily commutes would significantly challenge the facility capacity and operation stability of traditional power systems. Simultaneous charging for the household chargers and large-scale PEVs will possibly result in ripples and spikes on the daily power demand. It is therefore important to dispatch economic emission loads under different time intervals and PEVs charging allocations.

However, very limited publications have concerned EELD problem considering the integration PEV charging. The charging load uncertainty of PEVs addresses more complexity for the power system scheduling tasks such as unit commitment and optimal power flow [23]. Yang et al. [28] studied the economic unit commitment of power systems integrating various renewable generations and plug-in electric vehicles, where only economic factor is considered. In ref. [7], an energy storage model was proposed with gridable vehicles for economic load dispatch in the smart grid, and the authors used weighing coefficients to transform two objectives into a single objective function. In ref. [26], the authors use the same transform method to solve dynamic economic/environmental dispatch considering multiple plug-in electric vehicle loads. However, the appropriate selection of these weights remains to be a key issue for system operators. It is necessary to perform dynamic multi-objective optimization to solve EELD problem considering multiple PEVs charging scenarios, providing a Pareto front with a series of optimal results.

The key contributions of this paper are as follows. Firstly, a novel multi-objective dynamic economic emission load dispatch problem namely MO-DEELDP is established, for the first time combining PEVs charging scenarios. Secondly, a novel dynamic non-dominated sorting multi-objective biogeography-based optimization (Dy-NSBBO) method is proposed, which combines change detection and memory-based selection strategies to strengthen the dynamic optimization performance. Further, the proposed Dy-NSBBO method is adopted to seek the optimal solutions of the MO-DEELDP problem without and with considering the penetration of PEVs charging scenarios, and the comprehensive analysis on the economic and environmental impact of various PEV charging scenarios on the MO-DEELDP problem is finally addressed.

The remainder of this paper is organized as follows. Section 2 formulates a novel mathematical model of the MO-DEELDP problem under PEV charging, followed by Section 3 where a new Dy-NSBBO to solve dynamic multi-objective optimization problem is proposed. Section 4 applies Dy-NSBBO to solve the MO-DEELDP problem, and then comprehensively evaluate the performance of the proposed method by comparing with other algorithms. Section 5 concludes the paper and presents future works.

2. Problem formulation of MO-DEELDP

This section first presents the problem formulation of MO-DEELDP (Section 2.1), and then describes four plug-in electric vehicle charging scenarios (Section 2.2).

2.1. Dynamic economic emission load dispatch

The mathematic model of the MO-DEELDP problem is formulated as a multi-objective optimization problem, which has two objectives: the generation cost and the emission cost should be minimized, and it is defined as follow.

$$\min F(P,t) = \text{Minimize}(F_1(P,t), F_2(P,t)) \tag{1}$$

where t is time, $P = (P_1, \cdots, P_n)$ is the power outputs of generation units and n is the number of generation units in power system, $F(P, t)$ represents the set of two objective functions with respect to the time t. $F_1(P, t)$ denotes the dynamic economic load dispatch, and $F_2(P, t)$ denotes the dynamic emission load dispatch.

In Equation (1), the MO-DEELDP problem is required to depend only on the time t at the time interval $[t, t+1)$, it keeps no change within such interval. By this way, the MO-DEELDP problem is composed of a series of interconnected static optimization problems, that is, at the tth time interval, it corresponds to the tth static optimization problem. This MO-DEELDP problem is a new mathematic model, and its task is to rapidly and effectively seek a balance between generation cost and emission cost for each time interval.

2.1.1. Dynamic economic load dispatch

The dynamic economic load dispatch is expressed as minimization of the generation cost of power system, which is defined as

$$\begin{aligned} F_1(P,t) = \sum_{i=1}^{n} F_i^{eco}(P_{it}) = \sum_{i=1}^{n} \Big[\Big(a_i P_{it}^2 + b_i P_{it} + c_i \Big) \\ + \Big| d_i \sin\Big(e_i \Big(P_i^{\min} - P_{it} \Big) \Big) \Big| \Big] \quad (\$/\text{h}) \end{aligned} \tag{2}$$

where P_{it} is the power output of the ith generation unit at the tth time interval and $P_i^{\min}$ is the minimum power output limit of the ith generation unit, $F_i^{eco}(P_{it})$ is the generation cost function of the ith generation unit and is usually expressed as a quadratic polynomial added sinusoidal function, which denotes valve-point loading effect [30], and a_i, b_i, c_i, d_i and e_i are the generation cost coefficients of the ith generation unit.

2.1.2. Dynamic emission load dispatch

The dynamic emission load dispatch is expressed as minimization of the emission cost released by power systems, which is defined as

$$\begin{aligned} F_2(P,t) &= \sum_{i=1}^{n} F_i^{emis}(P_{it}) \\ &= \sum_{i=1}^{n} \Big[\Big(\alpha_i P_{it}^2 + \beta_i P_{it} + \gamma_i \Big) + \eta_i \exp(\delta_i P_{it}) \Big] \quad (\text{Kg/h}) \end{aligned} \tag{3}$$

where $F_i^{emis}(P_{it})$ is the emission cost function of the ith generation unit and is usually expressed as a quadratic polynomial associated with an exponential term [17], and $\alpha_i, \beta_i, \gamma_i, \eta_i$ and δ_i are the emission cost coefficients of the ith generation unit.

2.1.3. Constraints

Furthermore, two objective functions must satisfy the following constraints.

a) Real power balance constraint

The sum of the generated power of all generation units at each time interval t must be equal to the sum of power demand response by the various loads and the total transmission network loss in the corresponding time interval.

$$\sum_{i=1}^{n} P_{it} = P_{Dt} + P_{Lt} + L_{Et} \tag{4}$$

where the loads include the general traditional load demand P_D and

Table 1
Four Plug-in electric vehicle charging scenarios.

Case 1: EPRI Charging Scenario							Case 2: Off-peak Charging Scenario						
Time	Probability Distribution						Time	Probability Distribution					
01:00–06:00	0.100	0.100	0.095	0.070	0.050	0.030	01:00–06:00	0.185	0.185	0.090	0.090	0.040	0.040
07:00–12:00	0.010	0.003	0.003	0.013	0.021	0.021	07:00–12:00	0	0	0	0	0	0
13:00–18:00	0.021	0.021	0.021	0.001	0.005	0.005	13:00–18:00	0	0	0	0	0	0
19:00–24:00	0.016	0.036	0.054	0.095	0.100	0.100	19:00–24:00	0	0	0	0	0.185	0.185
Case 3: Peak Charging Scenario							Case 4: Stochastic Charging Scenario						
Time	Probability Distribution						Time	Probability Distribution					
01:00–06:00	0	0	0	0	0	0	01:00–06:00	0.057	0.049	0.048	0.024	0.026	0.097
07:00–12:00	0	0	0	0	0	0	07:00–12:00	0.087	0.048	0.011	0.032	0.021	0.057
13:00–18:00	0.185	0.185	0.185	0.185	0.090	0.090	13:00–18:00	0.038	0.022	0.021	0.061	0.032	0.022
19:00–24:00	0.040	0.040	0	0	0	0	19:00–24:00	0.028	0.022	0.055	0.025	0.035	0.082

the charging load L_E of PEVs, which is a new extra load type and will be further addressed in section 2.2. P_L is the transmission network loss, which can be expressed by B-coefficients and generation unit output as

$$P_{Lt} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_{it} B_{ij} P_{jt} \tag{5}$$

where B_{ij} is the transmission network loss coefficients which may be assumed to be constant under normal operating condition. The detailed procedure of B coefficients calculation could be found in Wood et al. [25] and Niu et al. [16].

b) Power capacity constraints

The power outputs of generation units should be within the capacity of each specific generation unit at each time interval t, so that

$$P_i^{\min} \le P_{it} \le P_i^{\max} \quad \text{for } i \in \{1, 2, \cdots, n\} \tag{6}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the lower limit and the upper limit of the ith power output respectively.

c) Ramp rate limit constraints

The power outputs of generation units should also be subject to the power ramp rate limits, that is, the power outputs cannot dramatically change between two adjacent intervals t and $t+1$, which is expressed as

$$\begin{cases} P_{it} - P_{i(t-1)} \le UR_i \\ P_{i(t-1)} - P_{it} \le DR_i \end{cases} \quad \text{for } i \in \{1, 2, \cdots, n\} \tag{7}$$

where UR_i and DR_i are the ramp-up rate limit and ramp-down rate limit of the ith power output respectively.

2.2. Plug-in electric vehicle charging scenarios

This section reviews four different PEV charging scenarios, and they have been described in Yang and Li et al. [26], in which they are modeled as static single-objective optimization problem by combining with economic emission load dispatch. In this paper, it is first reformulated as a dynamic multi-objective optimization problem based on the practical demand of power system.

These four PEV charging scenarios include respectively: (1) Electric Power Research Institute (EPRI) [9] charging scenario, which describes an aggregate probability distribution of PEV charging load; (2) off-peak charging scenario, which assumes that PEV are charging during off-peak time throughout the whole day; (3) peak charging scenario, which assumes that PEV are charging during peak time throughout the whole day; and [4] stochastic charging scenario, which assumes that some urgent and fast charging situations at random time interval throughout the whole day. The proposed four PEV charging scenarios are shown in Table 1, which are used to impose extra load L_{Et} in real power balance constraints [4].

3. Proposed approach

This section describes a dynamic non-dominated multi-objective biogeography-based optimization (Dy-NSBBO) algorithm. It is based on biogeography-based optimization (BBO), and some operators of BBO including migration and mutation, referring to Ma et al. [13] and Simon [20,21].

Inspired by the dynamic non-dominated sorting genetic algorithm II (Dy-NSGA-II) [3], which is the dynamic version of the original and successful static multi-objective evolutionary algorithms [22,6], standard BBO is changed to the dynamic multi-objective BBO. The flowchart of Dy-NSBBO algorithm is shown in Fig. 1, and the basic procedures are summarized as follows.

Step 1. Randomly initialize a population P, and evaluate the cost values of solutions in P.
Step 2. Based on non-dominated sorting procedure [6], store non-dominated solutions into the archive set A.
Step 3. If the termination criterion is not met, go to step 4; otherwise, terminate. Here the termination criterion is the maximum number of function evaluations, and the archive A is the output of Dy-NSBBO after termination.
Step 4. Create offspring population O using BBO migration [20], and randomly select solutions from parent population P as a set of sentry solutions, then re-evaluate their cost values to detect changes.
Step 5. Perform change detection strategy (which will be described in the following subsection 3.1) for the sentry solutions, and if a change has occurred, re-evaluate the cost values of the archived solutions in A, and retrieve some archived solutions based on a memory-based selection strategy (which will be described in the following subsection 3.2) and insert into population P. Otherwise, evaluate the cost values of solutions in offspring population O, and update population P based on non-dominated sorting level.
Step 6. Update non-dominated solutions in the archive A using the new population P, that is, a solution in P is inserted into the archive A if it dominates one or more existing solutions in A.

In this basic procedure of Dy-NSBBO, several subsequent components are discussed in detailed in the following subsections.

3.1. Change detection

The first component is to detect change of the cost values of sentry solutions. In every generation, 10% of the parent solutions are randomly selected to construct the sentry set. The cost values of these solutions including the objective function values $F(x,\ t)$ and the constraint values $G(x,\ t)$ are re-evaluated. If the new values are different from the old ones, a change has occurred. The process of change detection is illustrated in Equation (8) for an M-objective, n-decision variable and M_0-constraint optimization problem with a sentry set size of N_0, which further considers the constraint based on the change detection process described in Azzouz et al. [3]. In this equation, *Test a* is to verify if at least one objective function value $F_i(x_j,\ t+1)$ or constraint value $G_i(x_j,\ t+1)$ for any sentry solution x_j is different from the old one $F_i(x_j,\ t)$ or $G_i(x_j,\ t)$. If it is the case, the objective vector $F(x_j)$ or the constraint vector $G(x_j)$ has been changed. *Test b* considers that a change occurs when at least one objective vector $F(x_j)$ or the constraint vector $G(x_j)$ has been changed.

$$
\begin{array}{llllll}
\text{Sentry solutions} & x_1=\left(x_1^1,x_1^2,\cdots,x_1^n\right) & x_2=\left(x_2^1,x_2^2,\cdots,x_2^n\right) & \cdots & x_{N_0}=\left(x_{N_0}^1,\ x_{N_0}^2,\cdots,x_{N_0}^n\right) & \\
\text{Time } t & \left\{\begin{array}{l}F(x_1,t)=(F_1(x_1,t),\cdots,F_M(x_1,t))\\ G(x_1,t)=(G_1(x_1,t),\cdots,G_{M_0}(x_1,t))\end{array}\right. & \left\{\begin{array}{l}F(x_2,t)=(F_1(x_2,t),\cdots,F_M(x_2,t))\\ G(x_2,t)=(G_1(x_2,t),\cdots,G_{M_0}(x_2,t))\end{array}\right. & \cdots & \left\{\begin{array}{l}F(x_{N_0},t)=(F_1(x_{N_0},t),\cdots,F_M(x_{N_0},t))\\ G(x_{N_0},t)=(G_1(x_{N_0},t),\cdots,G_{M_0}(x_{N_0},t))\end{array}\right. & \text{Time } t+1
\end{array}
$$

$$
\underbrace{\times\ \underbrace{\left\{\begin{array}{l}F(x_1,t+1)=(F_1(x_1,t+1),\cdots,F_M(x_1,t+1))\\ G(x_1,t+1)=(G_1(x_1,t+1),\cdots,G_{M_0}(x_1,t+1))\end{array}\right.}_{test\ \ a}\ \underbrace{\left\{\begin{array}{l}F(x_2,t+1)=(F_1(x_2,t+1),\cdots,F_M(x_2,t+1))\\ G(x_2,t+1)=(G_1(x_2,t+1),\cdots,G_{M_0}(x_2,t+1))\end{array}\right.}_{test\ \ a}\cdots\underbrace{\left\{\begin{array}{l}F(x_{N_0},t+1)=(F_1(x_{N_0},t+1),\cdots,F_M(x_{N_0},t+1))\\ G(x_{N_0},t+1)=(G_1(x_{N_0},t+1),\cdots,G_{M_0}(x_{N_0},t+1))\end{array}\right.}_{test\ \ a}}_{test\ \ b} \tag{8}
$$

3.2. Memory-based selection strategy

There are many selection methods existing in dynamic evolutionary algorithms to deal with the environment changes of optimization problems. When there are only slight changes or periodic changes, there can be a large correlation between the optimal solutions after a change and the previous ones. In such case, the memory-based selection strategy is a very useful method, which makes use of past optimal solutions. In fact, when the change degree is small, information gained from the previous run can be exploited and reused to accelerate the convergence speed. In this paper, the memory-based selection strategy is used in the proposed Dy-NSBBO because power demand response of dynamic economic emission load dispatch with plug-in electric vehicle does not drastically change, and sometime they are periodic. Since the population contains a large number of solutions, it may be difficult to store and exploit the useful past information. Thus, the memory-based selection strategy uses the archive of best discovered solutions. That is, the memory-based selection strategy stores good solutions in an archive, and whenever a cost value change is detected, solutions are randomly retrieved from the archive and inserted into the population. If the cost value changes to a previously-encountered one, the solutions from the archive will be good solutions and the proposed Dy-NSBBO will converge very quickly to the new prominent regions.

4. Simulations and results

The proposed Dy-NSBBO algorithm has been applied in three different case studies to verify its feasibility. These are a 6-unit economic emission load dispatch without PEVs, a 6-unit economic emission load dispatch with PEVs, and a 10-unit economic emission load dispatch with PEVs. It should be noted that one 'unit' illustrates a fossil fuel based generator in power plants. To show the effectiveness of the proposed algorithm, it is compared with Dy-NSGA-II. Also note that we do not compare the proposed algorithm with other well-known evolutionary algorithms due to that there are no literature reported. The parameters of Dy-NSBBO and Dy-NSGA-II refer to Ma and Su et al. [12] and Azzouz et al. [3] respectively.

4.1. Case 1: 6-unit economic emission load dispatch without PEVs

In this case, a 6-unit economic emission load dispatch without PEVs is used to test the effectiveness of the proposed algorithm. The general traditional load demand is set to $P_D = 500$MW, and other coefficients of the generation units are given in Table A1 in appendix [8]. In this case, the optimization problems are static because the real power balance constraint is fixed without the charging loads of PEVs, namely, the dynamic multi-objective optimization problem is changed to the static one. The optimization results are shown in Fig. 2. It is seen from Fig. 2 that Dy-NSBBO almost performs the same as Dy-NSGA-II based on the distributions of generation cost and emission cost.

Furthermore, the optimization results are summarized in Table 2. It is seen from Table 2 that Dy-NSBBO outperforms the traditional Dy-NSGA-II due to the less cost on both generation and emission aspects. Specifically, the result achieved by proposed Dy-NSBBO algorithm is 34141.32$/h and 709.26 kg/h, successfully reducing 72.93$ and 2.06 Kg per hour compared with those achieved by the counterpart method. Even such 0.2%–0.3% cost saving would be potential to bring millions of dollars cost saving per year considering the significant generation scale. Based on these results, the proposed Dy-NSBBO algorithm is competitive for solving MO-DEELDP problem without PEVs and therefore selected as the computational tool for evaluating 6-unit and 10-unit MO-DEELDP problems.

4.2. Case 2: 6-unit economic emission load dispatch with PEVs

In this case, a 6-unit economic emission load dispatch with PEVs is used to test the effectiveness of the proposed algorithm. Four charging scenarios of PEVs described in section 2.2 are applied to this case. Given that charging load is varied with the time, the case 1 dynamically dispatches the generation production. Suppose there

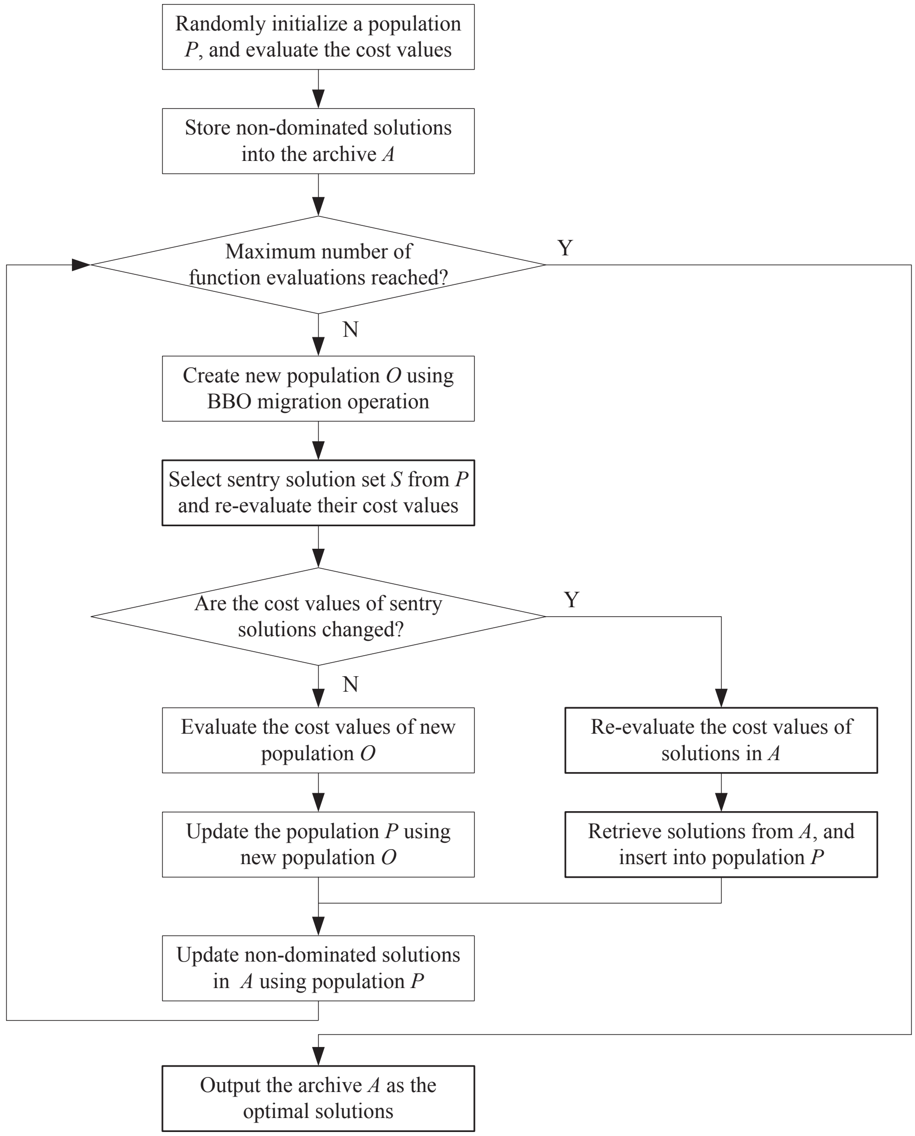

Fig. 1. Flowchart of Dy-NSBBO algorithm.

are 40,000 PEVs in a 24-h period, 45% of which are low hybrid vehicles equipped with 15kWh batteries, 25% of which are medium hybrid vehicles equipped with 25kWh batteries, and 30% of which are pure electric vehicles equipped with 40kWh batteries. The total PEV charging load for one day is calculated as $L_e = 40000 \times (15 \times 45\% + 25 \times 25\% + 40 \times 30\%) = 1000\text{MW}$. This is a considerable charging load for current grid level. However, the fast developing battery technology has quickly increased the capacity as large as over 90kWh, due to which our battery capacity assumption is reasonably conservative. Given the charging load distributions, the optimization results of the proposed Dy-NSBBO are shown in Fig. 3. Note that to clearly show the results, only four representative time intervals are selected and presented in each sub-figure.

It is clearly seen from Fig. 3 that for four selected time intervals of four PEV charging scenarios, Dy-NSBBO can effectively track the time-varying environments and obtain the satisfactory distributions of objective function values. In Fig. 3a and b, both charging profiles assume that the PEVs are heavily being charged during evening time, given which the original off-peak load demand will be reshaped as high load demand time and endure high charging cost. In Fig. 3c, according to charging profile assumption in Table 1,

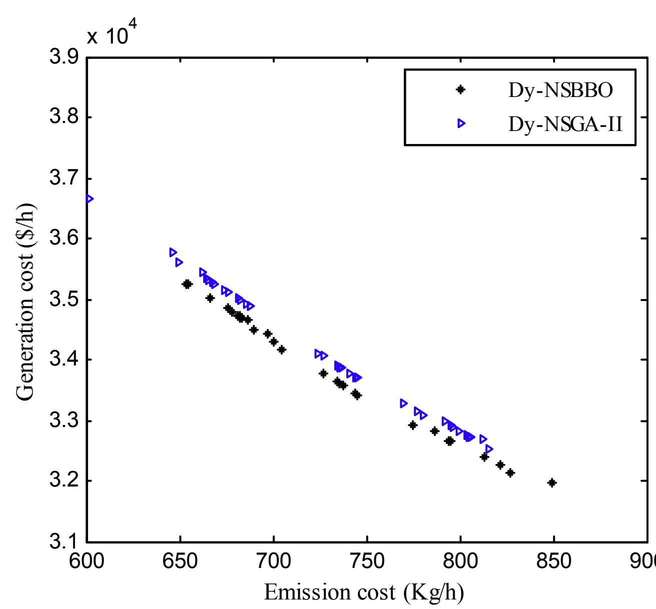

Fig. 2. Optimization results of Dy-NSBBO and Dy-NSGA-II.

Table 2
Best power outputs of generation units and optimal objective function values (500 MW).

Unit power output	Best solutions	
	Dy-NSBBO	Dy-NSGA-II
P_1 (MW)	173.11	165.87
P_2 (MW)	149.52	158.13
P_3 (MW)	65.36	78.78
P_4 (MW)	47.41	55.44
P_5 (MW)	30.07	22.61
P_6 (MW)	34.51	19.23
Generation cost ($/h)	34141.32	34214.25
Emission cost (Kg/h)	709.26	711.32

the peak loads of PEVs are due to be delivered from 13:00. Therefore the cost in 13:00 is much higher than that in 12:00 when 0 MW of PEV is assumed. On the other hand, Fig. 3d illustrates the combination of the original load demand and a stochastic PEVs charging profile, which sees a more random situation in both generation and emission cost. The results in Fig. 3 show that the significant integration of PEVs has considerable impact on the original load demand situation, by reshaping the demand curve in a 24 h time horizon. The best suited charging scenarios strongly rely on the dispatching results which is compared elaborately in Table A3 that the off-peak charging scenario turn out to be the lowest cost one.

Furthermore, Table A3 shows the comparison results of the proposed Dy-NSBBO and Dy-NSGA-II in different time intervals for four PEV charging scenarios. It could also be observed from Table A3 that the off-peak scenario sees the lowest cost 835211$/day among the four scenarios achieved by the proposed method, whereas the highest cost could be found by peak scenario as much as 852666$/day. EPRI and stochastic scenarios see 836509$/day and 849959$/day respectively. Similar situation could be found in the

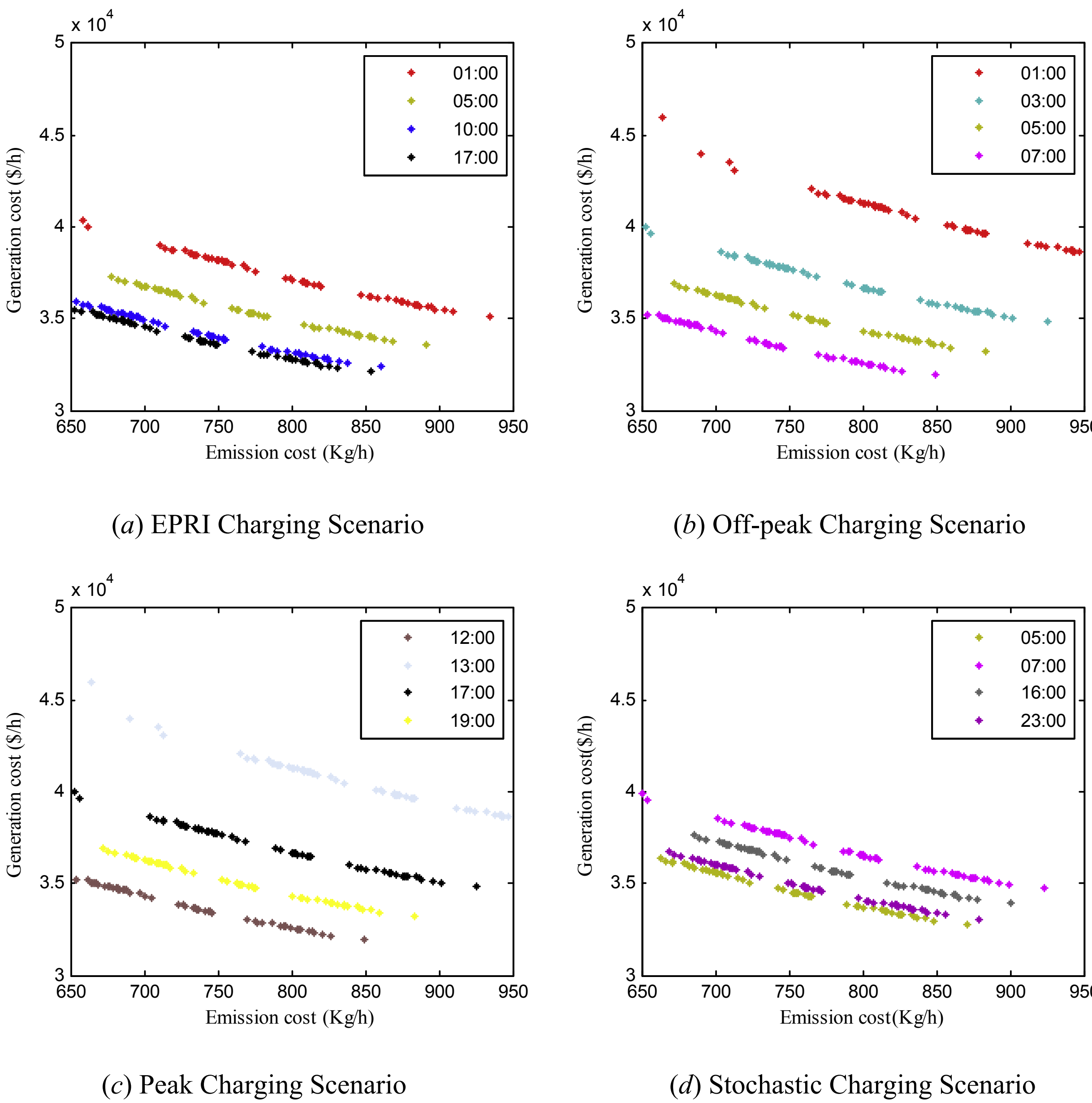

Fig. 3. Optimization results of Dy-NSBBO for four PEV charging scenarios in four different time intervals.

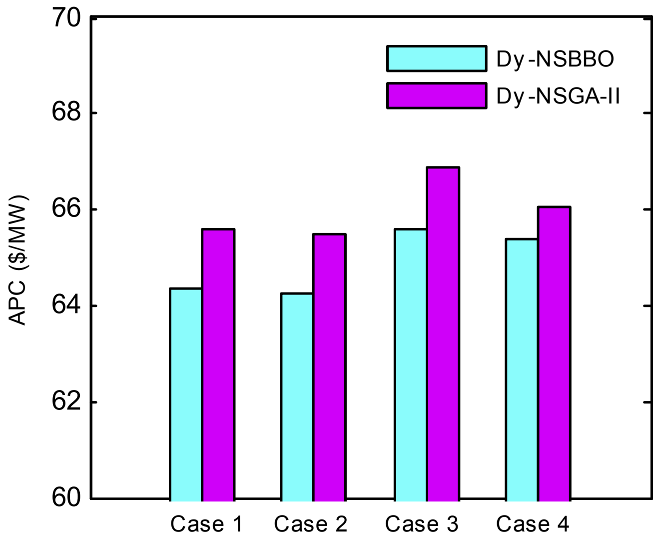

Fig. 4. Comparison of APC for Dy-NSBBO and Dy-NSGA-II in 6-unit case under four charging scenarios.

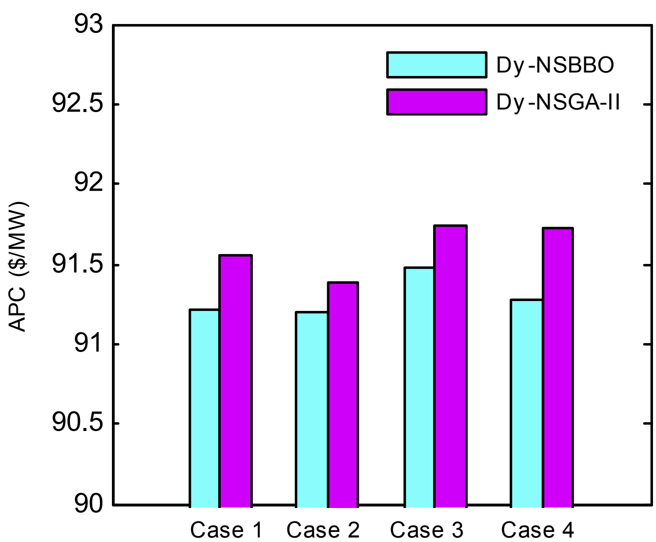

Fig. 5. Comparison of APC for Dy-NSBBO and Dy-NSGA-II in 10-unit case under four charging scenarios.

emission cost comparison that the lowest emission is 18250 Kg/day. The average power cost (APC) [28] showed in (9) is adopted to evaluate the economic efficiency for comparing the performance of proposed algorithm. Fig. 4 shows the comparison of APC for four scenarios solved by the two algorithms. In all four scenarios, Dy-NSBBO achieves better APC results by 64–66 $/MW, outperforming the 66–68 $/MW achieved by Dy-NSGA-II. The APC of the off-peak scenario is 64.25$/MW, with 1.3$/MW lower than peak scenario result.

$$APC = \frac{Generation\ \ Cost}{Generation\ \ Power} = \frac{F_1}{P_D + P_L + L_E} \tag{9}$$

4.3. Case 3: 10-unit economic emission load dispatch with PEVs

To further verify the effectiveness of the proposed algorithm, a 10-unit economic emission load dispatch with PEVs is used. Compared with case 2, it is a large scale case with high dimensional solution decision variables. The general traditional load demand is set as $P_D = 900$MW, and other coefficients of the generation units are given in Table A2 in appendix. This case still uses four charging scenarios of PEVs described in the above case studies. The comparison results of the proposed Dy-NSBBO and Dy-NSGA-II in different time intervals for four PEV charging scenarios are shown in Table A4, and the comparison of APC for the four scenarios are shown in Fig. 5.

It is seen from Table A4 that for all the four PEV charging scenarios, the proposed Dy-NSBBO again performs better than Dy-NSGA-II on both generation and emission cost in 10-unit case. Meanwhile, among these four PEV charging scenarios results achieved by the proposed Dy-NSBBO, the off-peak charging scenario has the smallest generation cost and the lowest emission cost with the total amount of 2061330 $/day and 153321 lb/day respectively. In addition, the lowest APC is 91.20 $/MW for off-peak charging scenario, which further illustrates off-peak charging scenario is the best scheme with respect to plug-in electric vehicles we study.

The comprehensive results analysis also demonstrates that PEVs charging scenarios have remarkable impact on both power system economic and emission cost. The policy makers are suggested to encourage the PEV users to charge their vehicles during off-peak load time period to avoid higher generation and emission cost.

5. Conclusions

In this paper, a dynamic economic emission load dispatch model is established with the integrations of plug-in electric vehicle charging scenarios as a constrained dynamic multi-objective optimization problem. A new dynamic non-dominated sorting biogeography-based optimization called Dy-NSBBO is proposed to solve the MO-DEELDP. The performance of Dy-NSBBO is investigated on three different cases, including a 6-unit economic emission load dispatch without PEVs, and 6-unit and 10-unit economic emission load dispatch with four PEV charging scenarios including EPRI charging scenario, off-peak charging scenario, peak charging scenario, and stochastic charging scenario. The numerical simulations show that the proposed Dy-NSBBO can effectively find optimal dynamic economic emission load dispatch with PEVs, and outperforms the well-known Dy-NSGA-II with respect to solving dynamic multi-objective optimization problem. The numerical simulations also show that for four PEV charging scenarios, the off-peak charging scenario has the advantage in reducing the generation cost and environmental pollutant emissions.

Future work will be addressed on developing the smart scheduling methods for flexible demand side management of PEVs to contribute to the integration of stochastic renewable energy generation. Moreover, the framework of algorithm presented in this paper could be extended for other types of evolutionary algorithms to solve dynamic multi-objective optimization problems in terms of economic and environmental load dispatch.

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Appendix A

Table A1
The generation cost coefficients $a,\ b,\ c$, the emission cost coefficients $\alpha,\ \beta,\ \gamma$, the capacity limits P^{min} and P^{max} of the generation units, and transmission network loss coefficient B in 6-unit case study.

Unit	Generation cost coefficients			Emission cost coefficients			P^{min} (MW)	P^{max} (MW)
	a ($/hMW^2)	b ($/hMW)	c ($/h)	α (Kg/hMW^2)	β (Kg/hMW)	γ (Kg/h)		
1	0.1525	38.5397	756.7989	0.0042	0.3277	13.8593	125	315
2	0.1059	46.1592	451.3251	0.0042	0.3277	13.8593	130	325
3	0.0280	40.3966	1049.9977	0.0068	−0.5455	40.2669	35	210
4	0.0355	38.3055	1243.5311	0.0068	−0.5455	40.2669	35	225
5	0.0211	36.3278	1658.5696	0.0046	−0.5112	42.8955	10	150
6	0.0180	38.2704	1356.6592	0.0046	−0.5112	42.8955	10	125

$$B = \begin{bmatrix} 0.002022 & -0.000286 & -0.000534 & -0.000565 & -0.000454 & -0.000103 \\ -0.000286 & 0.003243 & 0.000016 & -0.000307 & -0.000422 & -0.000147 \\ -0.000533 & 0.000016 & 0.002085 & 0.000831 & 0.000023 & -0.000270 \\ -0.000565 & -0.000307 & 0.000831 & 0.001129 & 0.000113 & -0.000295 \\ -0.000454 & -0.000422 & 0.000023 & 0.000113 & 0.000460 & -0.000153 \\ 0.000103 & -0.000147 & -0.000270 & -0.000295 & -0.000153 & 0.000898 \end{bmatrix}$$

Table A2
The generation cost coefficients $a,\ b,\ c,\ d,\ e$, the emission cost coefficients $\alpha,\ \beta,\ \gamma,\ \eta,\ \delta$, the capacity limits P^{min} and P^{max}, the ramp rate limit UR and DR of the generation units, and transmission network loss coefficient B in 10-unit case study.

Unit	Generation cost coefficients					Emission cost coefficients					P^{min} (MW)	P^{max} (MW)	DR (MW/h)	UR (MW/h)
	a ($/(hMW^2)	b ($/hMW)	c ($/h)	d ($/h)	e (rad/MW)	α (lb/hMW^2)	β (lb/hMW)	γ (lb/h)	η (lb/h))	δ (MW^{-1})				
1	0.1524	38.5397	786.7988	450	0.041	0.0312	−2.4444	103.3908	0.5035	0.0207	150	470	80	80
2	0.1058	46.1591	4513.251	600	0.036	0.0312	−2.4444	103.3908	0.5035	0.0207	135	470	80	80
3	0.0280	40.3965	1049.998	320	0.028	0.0509	−4.0695	300.3910	0.4968	0.0202	73	340	80	80
4	0.0354	38.3055	1243.531	260	0.052	0.0509	−4.0695	300.3910	0.4968	0.0202	60	300	50	50
5	0.0211	36.3278	1658.570	280	0.063	0.0344	−3.8132	320.0006	0.4972	0.0200	73	243	50	50
6	0.0179	38.2704	1356.659	310	0.048	0.0344	−3.8132	320.0006	0.4972	0.0200	57	160	50	50
7	0.0121	36.5104	1450.705	300	0.086	0.0465	−3.9023	330.0056	0.5163	0.0214	20	130	30	30
8	0.0121	36.5104	1450.705	340	0.082	0.0465	−3.9023	330.0056	0.5163	0.0214	47	120	30	30
9	0.1090	39.5804	1455.606	270	0.098	0.0465	−3.9524	350.0056	0.5475	0.0234	20	80	30	30
10	0.1295	40.5407	1469.403	380	0.094	0.0470	−3.9864	360.0012	0.5475	0.0234	10	55	30	30

$$B = 10^{-4} \cdot \begin{bmatrix} 0.49 & 0.14 & 0.15 & 0.15 & 0.16 & 0.17 & 0.17 & 0.18 & 0.19 & 0.20 \\ 0.14 & 0.45 & 0.16 & 0.16 & 0.17 & 0.15 & 0.15 & 0.16 & 0.18 & 0.18 \\ 0.15 & 0.16 & 0.39 & 0.10 & 0.12 & 0.12 & 0.14 & 0.14 & 0.16 & 0.16 \\ 0.15 & 0.16 & 0.10 & 0.40 & 0.14 & 0.10 & 0.11 & 0.12 & 0.14 & 0.15 \\ 0.16 & 0.17 & 0.12 & 0.14 & 0.35 & 0.11 & 0.13 & 0.13 & 0.15 & 0.16 \\ 0.17 & 0.15 & 0.12 & 0.10 & 0.11 & 0.36 & 0.12 & 0.12 & 0.14 & 0.15 \\ 0.17 & 0.15 & 0.14 & 0.11 & 0.13 & 0.12 & 0.38 & 0.16 & 0.16 & 0.18 \\ 0.18 & 0.16 & 0.14 & 0.12 & 0.13 & 0.12 & 0.16 & 0.40 & 0.15 & 0.16 \\ 0.19 & 0.18 & 0.16 & 0.14 & 0.15 & 0.14 & 0.16 & 0.15 & 0.42 & 0.19 \\ 0.20 & 0.18 & 0.16 & 0.15 & 0.16 & 0.15 & 0.18 & 0.16 & 0.19 & 0.44 \end{bmatrix}$$

Table A3
Comparison results of optimal objective function values for Dy-NSBBO and Dy-NSGA-II in 6-unit case study with four charging scenarios. Note that in the last row generation cost and emission cost show the total values, and APC shows the average value for a 24-h period in one day.

Time	Case 1: EPRI Charging Scenario						Case 2: Off-peak Charging Scenario					
	Dy-NSBBO			Dy-NSGA-II			Dy-NSBBO			Dy-NSGA-II		
	Gen. cost ($/h)	Emi. cost (Kg/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (Kg/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (Kg/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (Kg/h)	APC ($/MW)
01:00	37618.14	807.48	62.69	37934.86	862.11	63.22	41728.47	815.66	60.91	42015.17	823.82	61.33
02:00	37322.43	811.52	62.20	37768.41	868.24	62.95	41763.58	812.42	60.96	42369.70	820.13	61.85
03:00	36947.19	785.19	62.09	37532.29	799.39	63.08	36527.29	795.15	61.91	36617.54	805.47	62.06
04:00	36142.28	732.76	63.40	37866.35	742.54	66.43	36518.31	794.30	61.89	36590.32	804.36	62.01
05:00	35764.65	775.25	65.02	36310.46	777.21	66.01	35043.65	766.62	64.89	35443.18	767.19	65.63
06:00	34350.17	768.17	64.81	34706.33	776.74	65.48	35000.79	762.87	64.81	35510.46	771.44	65.76
07:00	33087.31	742.78	64.87	33521.21	758.16	65.72	33824.43	741.55	67.64	34124.55	747.24	68.24
08:00	33314.66	740.49	66.23	33954.57	760.45	66.50	33740.26	744.41	67.48	34130.19	751.32	68.26
09:00	33378.42	741.35	66.35	33677.44	762.73	66.95	33712.54	742.80	67.42	33887.42	749.49	67.77
10:00	33053.90	743.96	64.43	33265.13	761.70	64.84	33710.32	741.61	67.42	33781.30	750.54	67.56
11:00	33924.77	752.14	65.11	34632.64	765.49	66.47	33774.19	742.22	67.54	33562.86	743.62	67.12
12:00	33927.15	753.82	65.12	34579.70	767.36	66.37	33710.24	743.09	67.42	33925.57	752.74	67.85
13:00	33939.16	753.71	65.14	34488.19	766.27	66.19	33711.48	742.53	67.42	33782.18	750.16	67.56
14:00	33917.44	754.96	65.10	34492.52	764.16	66.20	33755.16	741.28	67.51	34225.62	758.73	68.45
15:00	33922.71	752.17	65.11	34536.36	765.45	66.28	33771.55	742.11	67.54	34162.51	746.19	68.32
16:00	32804.58	736.23	65.47	32448.27	748.32	64.76	33745.97	742.42	67.49	34551.13	749.28	69.10
17:00	33516.33	747.90	66.37	34816.41	753.44	68.94	33740.12	743.30	67.48	33890.74	752.40	67.78
18:00	33442.17	742.18	66.22	34821.89	750.17	68.95	33794.34	741.78	67.58	34443.20	751.15	68.88
19:00	33840.85	750.25	65.58	34254.16	762.50	66.38	33745.90	741.26	67.49	34424.83	749.46	68.84
20:00	34357.41	760.59	64.10	35340.30	772.32	65.93	33707.65	742.10	67.41	34552.12	744.31	69.10
21:00	35891.95	779.67	64.79	36521.72	780.78	65.92	33748.49	743.54	67.49	34340.47	745.20	68.68
22:00	36972.04	788.14	62.14	37865.80	796.16	63.64	33709.16	743.28	67.41	34427.13	752.66	68.85
23:00	37601.32	810.32	62.67	37964.24	802.20	63.27	41747.34	811.22	60.94	41889.57	821.42	61.15
24:00	37472.89	806.56	62.45	37801.50	811.35	63.00	41728.20	812.16	60.91	41902.66	819.13	61.17
Total	836509	18327	64.35	852419	18542	65.57	835211	18250	64.25	851100	18425	65.47
Time	Case 3: Peak Charging Scenario						Case 4: Stochastic Charging Scenario					
	Dy-NSBBO			Dy-NSGA-II			Dy-NSBBO			Dy-NSGA-II		
	Gen. cost ($/h)	Emi. cost (Kg/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (Kg/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (Kg/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (Kg/h)	APC ($/MW)
01:00	33714.98	742.43	67.42	33978.85	753.63	67.95	35780.79	778.22	64.23	36665.36	783.30	65.82
02:00	33790.43	741.22	67.58	34316.13	758.15	68.63	35751.32	775.37	65.12	36322.54	778.42	66.16
03:00	33724.10	741.18	67.44	34771.41	751.42	69.54	35747.16	774.16	65.23	36410.13	775.17	66.44
04:00	33707.45	742.35	67.41	34655.23	759.13	69.31	33907.65	753.44	64.70	34053.22	760.52	64.98
05:00	33740.67	743.47	67.48	34548.19	753.62	69.09	33940.24	758.56	64.52	34095.47	767.34	64.82
06:00	33710.91	742.29	67.42	34342.75	750.47	68.68	37632.10	809.31	63.03	37708.25	802.16	63.16
07:00	33742.32	741.15	67.48	34449.10	749.23	68.89	36521.96	796.68	62.21	37180.34	800.32	63.33
08:00	33721.12	742.28	67.44	34875.55	752.52	69.75	35902.57	779.42	65.51	36224.75	781.18	66.10
09:00	33715.85	742.54	67.43	34650.32	751.40	69.30	33082.62	743.35	64.74	33972.65	751.74	66.48
10:00	33702.24	743.61	67.40	34754.10	756.18	69.50	33997.11	758.26	63.90	34331.22	763.42	64.53
11:00	33798.65	742.23	67.59	34112.74	748.33	68.22	33900.42	750.77	65.06	34853.10	757.55	66.89
12:00	33705.17	742.45	67.41	34254.86	751.46	68.50	35726.89	778.18	64.14	36716.06	785.13	65.91
13:00	41728.43	815.97	60.91	42250.13	826.74	61.67	35001.04	761.24	65.05	36565.59	770.84	67.96
14:00	41707.28	818.16	60.88	42562.41	824.28	62.13	33921.17	755.61	64.98	34842.63	768.16	66.74
15:00	41710.90	816.43	60.89	42995.52	818.19	62.76	33999.53	759.79	65.25	34530.41	767.54	66.27
16:00	41704.12	816.80	60.88	42766.16	820.20	62.43	33472.26	758.56	59.66	34974.85	762.38	62.34
17:00	36527.47	795.16	61.91	36772.32	804.34	62.32	33906.58	755.72	63.73	34321.69	761.21	64.51
18:00	36508.28	792.72	61.87	36751.74	808.16	62.29	33920.19	755.80	64.98	34834.64	767.43	66.73
19:00	36543.55	793.45	67.67	36523.68	809.50	67.63	33980.66	757.25	64.35	34053.25	762.19	64.49
20:00	36518.23	798.66	67.62	36719.43	800.13	67.99	33913.52	755.44	64.96	34806.78	769.80	66.67
21:00	33774.60	745.14	67.54	34438.71	810.54	68.87	35768.32	774.15	64.44	36311.14	787.47	65.42
22:00	33725.88	741.50	67.45	34575.22	807.20	69.15	33929.80	750.69	64.62	34916.32	751.66	66.50
23:00	33724.53	742.12	67.44	34712.34	805.79	69.42	35006.65	764.27	65.43	36517.60	772.12	68.25
24:00	33718.90	743.74	67.43	34633.15	806.14	69.26	36500.23	790.32	62.71	37223.42	797.63	63.95
Total	852666	18395	65.59	869407	18772	66.88	849959	18338	65.38	858547	18669	66.04

Note: This table is continued by Table A3.

Table A4
Comparison results of optimal objective function values for Dy-NSBBO and Dy-NSGA-II in 10-unit case study under four charging scenarios. Note that in the last row generation cost and emission cost show the total values, and APC shows the average value for a 24-h period in one day.

Time	Case 1: EPRI Charging Scenario						Case 2: Off-peak Charging Scenario					
	Dy-NSBBO			Dy-NSGA-II			Dy-NSBBO			Dy-NSGA-II		
	Gen. cost ($/h)	Emi. cost (lb/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (lb/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (lb/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (lb/h)	APC ($/MW)
01:00	90731.14	6786.31	90.73	90828.82	6871.91	90.82	97873.51	7160.64	90.20	97602.34	7354.34	89.95
02:00	83307.68	6231.06	83.30	83330.83	6320.66	83.33	97774.01	7103.04	90.11	98450.96	7227.35	90.73
03:00	84215.00	6298.92	84.63	84741.45	6363.03	85.16	89963.24	6704.87	90.87	90369.94	6710.94	91.28
04:00	83802.58	6268.07	86.39	84493.62	6318.12	87.10	89222.72	6712.03	90.12	90688.14	6732.33	91.60
05:00	90731.14	6786.33	95.50	91336.61	6800.47	96.14	85837.78	6397.26	91.31	86013.12	6438.63	91.50
06:00	82730.30	6187.87	88.95	83882.43	6218.39	90.19	85118.66	6301.14	90.55	85742.73	6465.12	91.21
07:00	84215.00	6298.92	92.54	84151.74	6344.76	92.47	82535.12	6101.15	91.70	83172.28	6261.88	92.41
08:00	85452.24	6391.46	94.63	85556.56	6498.80	94.74	82183.28	6145.43	91.31	82994.98	6212.63	92.21
09:00	90318.73	6755.46	98.02	90835.27	6805.55	98.59	82692.29	6191.92	91.88	82693.82	6299.13	91.88
10:00	82730.31	6187.87	90.61	82730.02	6261.96	90.61	82617.13	6189.22	91.79	82942.61	6228.55	92.15
11:00	84215.14	6298.92	91.43	85080.29	6392.97	92.37	82713.17	6140.34	91.90	82896.46	6253.54	92.10
12:00	86936.93	6502.51	94.39	87636.59	6554.98	95.15	82345.78	6154.72	91.49	82607.73	6264.05	91.78
13:00	88256.66	6601.22	95.82	88401.62	6726.05	95.98	82482.86	6169.37	91.64	82561.95	6269.21	91.73
14:00	83555.13	6249.57	90.72	84128.49	6258.35	91.34	82709.94	6149.31	91.89	82872.87	6204.07	92.08
15:00	82565.34	6175.53	89.64	83265.15	6256.45	90.40	82022.27	6118.05	91.13	82456.00	6218.41	91.61
16:00	90318.73	6755.46	98.24	91888.04	6833.38	99.98	82444.68	6157.37	91.60	82584.32	6219.93	91.76
17:00	86607.12	6477.83	95.69	86651.54	6563.60	95.74	82874.43	6183.87	92.08	82946.74	6263.51	92.16
18:00	84215.74	6298.92	93.05	85191.09	6376.43	94.13	82155.84	6134.29	91.28	82880.24	6212.49	92.08
19:00	82895.27	6200.21	90.49	83236.69	6351.77	90.86	82551.67	6160.34	91.72	82983.96	6226.02	92.20
20:00	90731.14	6786.34	96.93	91172.94	6880.65	97.40	82519.99	6178.14	91.68	82430.27	6246.69	91.58
21:00	84957.34	6354.45	89.05	85100.87	6445.88	89.20	82687.26	6155.65	91.87	82726.68	6278.24	91.91
22:00	84215.32	6298.92	84.63	84494.54	6312.59	84.91	82976.43	6101.22	92.19	83066.48	6254.94	92.29
23:00	82895.27	6200.21	82.89	83271.31	6208.43	83.27	97804.62	7289.13	90.14	97783.07	7314.94	90.12
24:00	90731.14	6786.36	90.73	91634.29	6842.13	91.63	97631.32	7223.35	89.98	97840.96	7302.96	90.17
Total	2061738	153483	91.22	2069298	155443	91.56	2061330	153321	91.20	2065476	154685	91.39
Time	Case 3: Peak Charging Scenario						Case 4: Stochastic Charging Scenario					
	Dy-NSBBO			Dy-NSGA-II			Dy-NSBBO			Dy-NSGA-II		
	Gen. cost ($/h)	Emi. cost (lb/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (lb/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (lb/h)	APC ($/MW)	Gen. cost ($/h)	Emi. cost (lb/h)	APC ($/MW)
01:00	82474.05	6188.95	91.63	82784.79	6244.82	91.98	87405.75	6501.76	91.33	87627.73	6567.74	91.56
02:00	82391.14	6117.06	91.54	82641.26	6249.65	91.82	89886.51	6686.30	94.71	89845.71	6681.61	94.67
03:00	82623.76	6179.32	91.80	82705.71	6282.04	91.89	85834.59	6384.89	90.54	86158.51	6391.15	90.88
04:00	82161.55	6155.46	91.29	82475.14	6281.39	91.63	85007.67	6323.38	91.99	85444.12	6325.35	92.47
05:00	82536.71	6114.42	91.70	82623.06	6250.56	91.80	86744.21	6452.55	93.67	86907.64	6520.56	93.85
06:00	82775.89	6113.61	91.97	82858.71	6251.77	92.06	86661.51	6446.40	86.92	86766.08	6569.35	87.02
07:00	82582.87	6196.55	91.75	82650.14	6294.06	91.83	84511.52	6286.47	85.62	85005.53	6239.08	86.12
08:00	82335.99	6153.35	91.48	82572.91	6223.84	91.74	84511.52	6286.47	89.14	85002.31	6283.98	89.66
09:00	82407.96	6136.96	91.56	82778.34	6206.81	91.97	86661.51	6446.41	95.12	86785.21	6551.94	95.26
10:00	82731.49	6115.86	91.92	82979.06	6265.13	92.19	83601.90	6218.81	89.70	83462.04	6250.01	89.55
11:00	82805.04	6177.56	92.00	82948.86	6270.69	92.16	84428.82	6280.32	91.67	84530.54	6292.68	91.78
12:00	82599.22	6174.68	91.77	82677.22	6204.21	91.86	87240.36	6489.46	91.16	87520.92	6474.27	91.45
13:00	97482.51	7227.97	89.84	97872.11	7335.75	90.20	84676.90	6298.77	90.27	84690.61	6321.51	90.28
14:00	97359.15	7240.84	89.73	97734.44	7327.91	90.07	85338.44	6347.98	92.55	85967.38	6322.48	93.24
15:00	97239.69	7204.75	89.62	97409.28	7325.04	89.77	87736.51	6526.37	95.26	87879.36	6514.95	95.41
16:00	97447.92	7294.58	89.81	97655.32	7335.87	90.00	84759.59	6304.92	88.19	85249.46	6352.03	88.70
17:00	89833.85	6720.74	90.74	89990.32	6855.37	90.89	84842.28	6311.07	91.03	84878.41	6496.59	91.07
18:00	89659.74	6739.48	90.56	89886.03	6844.74	90.79	84428.82	6280.32	91.57	84730.55	6308.01	91.89
19:00	85364.26	6337.82	90.81	85469.05	6464.49	90.92	85338.44	6347.92	91.95	85019.02	6399.69	91.61
20:00	85269.14	6318.31	90.71	85685.52	6452.43	91.15	85586.52	6366.44	92.82	86094.14	6385.44	93.37
21:00	82863.44	6177.21	92.07	82875.02	6228.85	92.08	90713.44	6747.81	94.98	91945.93	6833.55	96.27
22:00	82244.28	6126.88	91.38	82364.21	6230.68	91.51	87405.75	6501.76	94.49	87675.75	6604.58	94.78
23:00	82913.62	6146.21	92.12	83200.91	6250.41	92.44	84511.52	6286.47	90.38	84589.65	6305.32	90.47
24:00	82803.29	6125.12	92.00	82655.91	6269.31	91.83	89473.05	6655.54	91.11	89482.81	6706.06	91.12
Total	2067307	154178	91.47	2073242	155932	91.74	2062806	153778	91.27	2073017	155801	91.72

Note: This table is continued by Table A4.

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