

# Demand side management of plug-in electric vehicles and coordinated unit commitment: A novel parallel competitive swarm optimization method

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## Abstract

Decreasing initial costs, the increased availability of charging infrastructure and favorable policy measures have resulted in the recent surge in plug-in electric vehicle (PEV) ownerships. PEV adoption increases electricity consumption from the grid that could either exacerbate electricity supply shortages or smooth demand curves. The optimal coordination and commitment of power generation units while ensuring wider access of PEVs to the grid are, therefore, important to reduce the cost and environmental pollution from thermal power generation systems, and to transition to a smarter grid. However, flexible demand side management (DSM) considering the stochastic charging behavior of PEVs adds new challenges to the complex power system optimization, and makes existing mathematical approaches ineffective. In this research, a novel parallel competitive swarm optimization algorithm is developed for solving large-scale unit commitment (UC) problems with mixed-integer variables and multiple constraints — typically found in PEV integrated grids. The parallel optimization framework combines binary and real-valued competitive swarm optimizers for solving the UC problem and demand side management of PEVs simultaneously. Numerical case studies have been conducted with multiple scales of unit numbers and various demand side management strategies of plug-in electric vehicles. The results show superior performance of proposed parallel competitive swarm optimization based method in successfully solving the proposed complex optimization problem. The flexible demand side management strategies of plug-in electric vehicles have shown large potentials in bringing considerable economic benefit.

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## 1 Nomenclature

2  $a_j, b_j, c_j$  Coefficients of fuel cost for unit  $j$

3  $F_{j,t}$  Fuel cost of unit  $j$  at time  $t$

4  $m$  Ratio coefficient

5  $MDT_j$  Minimum down time of unit  $j$

6  $MUT_j$  Minimum up time of unit  $j$

7  $n$  Number of units

8  $Np$  Number of particles

9  $P_{D,t}$  Power demand at time  $t$

10  $P_{j,max}$  Maximum power limits of unit  $j$

11  $P_{j,min}$  Minimum power limits of unit  $j$

12  $P_{j,t}$  Determined power of unit  $j$  at time  $t$

13  $P_{PEV,t,max}$  Maximum charging power of PEVs at time  $t$

14  $P_{PEV,t,min}$  Minimum charging power of PEVs at time  $t$

15  $P_{PEV,total}$  Total necessary charging power

16  $P_{PEV,t}$  Demand side management of PEVs at time  $t$

17  $P_{PEVload,t}$  Uncoordinated charging load of PEVs at time  
18  $t$

19  $S(V_{l,k})$  V-shape transfer function

20  $SR_t$  Spinning reserves at time  $t$

21  $SUC_{j,t}$  Cold-start cost of unit  $j$  at time  $t$

22  $SUH_{j,t}$  Hot-start cost of unit  $j$  at time  $t$

23  $SU_{j,t}$  Start-up cost of unit  $j$  at time  $t$

24  $T$  Total scheduling hours

25  $T_{cold,j}$  Cold-start hour of unit  $j$

26  $TOFF_{j,t}$  Off-line duration time of unit  $j$

27  $TON_{j,t}$  On-line duration time of unit  $j$

28  $TPC_{Tn}$  Total economic cost

29  $u_{j,t}$  Binary status of unit  $j$  at time  $t$

30  $V_{l,k}, V_{w,k}$  Velocity of the losers and winners in the  $k^{th}$  com-  
31 petition

32	$w$	Weighting factor of PEVs charging load
33	$X'_{b,k}(t)$	Mean position value of the whole binary swarm particles
34		
35	$X'_k(t)$	Mean position value of the whole swarm particles
36	$X_{b,l,k}, X_{b,w,k}$	Position of the binary losers and winners in the $k^{th}$ competition
37		
38	$X_{l,k}, X_{w,k}$	Position of the losers and winners in the $k^{th}$ competition
39		
40	ACO	Ant colony optimization
41	BCSO	Binary competitive swarm optimization
42	BDE	Binary differential evolution
43	BGSO	Binary glowworm swarm optimization
44	BLPSO	Best parallel particle swarm optimization
45	BPSO	Binary particle swarm optimization
46	brGA	Binary-real-code genetic algorithm
47	CSO	Competitive swarm optimizer
48	DBDE	Discrete binary differential evolution
49	DCSO	Dynamic competitive particle swarm optimizer
50	DE	Differential evolution
51	GAs	Genetic algorithms
52	HPSO	Hybrid particle swarm optimizer
53	IBSO	Improved binary particle swarm optimization
54	ICSO	Improved competitive swarm optimization
55	IPSO	Improved particle swarm optimization
56	MA	Meta-heuristic algorithms
57	MCSO	Modified competitive swarm optimizer
58	NBPSO	New binary particle swarm optimization
59	OLCSO	Orthogonal learning competitive swarm optimizer
60	PSO	Particle swarm optimization
61	QPSO	Quantum-inspired particle swarm optimization
62	SA	Simulated annealing

## 63 1. Introduction

65 Transport accounted for around 29% of global final energy demand and 7.7Gt of energy related CO<sub>2</sub> emissions [1]. Sectoral CO<sub>2</sub>-equivalent emissions of 7.0 GtCO<sub>2</sub>e and 7.7 GtCO<sub>2</sub>e were reported for 2010 [2] and 2015 [3] respectively. The sector is responsible for over a quarter of all greenhouse gas emissions in Europe [4]. European transport emissions have increased by a quarter since 1990 [5] and are continuing to rise across the world in spite of more efficient vehicles and policies [2]. Reasons include but not limited to, the continuing growth in passenger and freight activity, which is strongly coupled with economic growth, especially in emerging economies. The progress in the adoption of renewable energy in the sector has also been slow. Compared to the other end-use sectors, the global share of renewable energy in transport is very small, at just 4% in 2015 [3]. Moreover, the use of renewable energy in transport is dominated by biofuels, with electricity accounting for around 1% of the total. Analysis suggests that national 2030 climate goals will be missed in Europe unless transport emissions are drastically reduced [5]. Passenger road transport needs to be entirely decarbonised to meet 2050 Paris climate commitments [7].

### 66 1.1. Motivation

67 Electrical power and energy systems are closely related to the engineering production and sustainability of ecological environment. The carbon emissions, environmental pollution and energy consumption caused by fossil energy-based thermal power generation and vehicle exhausts are becoming increasingly serious [6], which significantly threatens the global climate and locality ecosystem. Current situation of the power systems are seeing large difficulties in achieving a temperature control target of 1.5 °C agreed in the Paris Climate Conference 2015 years [7]. Power system operation has long been a crucial task in delivering the economic and environmental goals [8], through which the smart coordination of power generation and load demand is promising to significantly contribute to the economic cost and green-house-gas (GHG) emission reductions [9]. On the other hand, among various types of load demand, plug-in electric vehicles (PEVs) are welcoming a tremendous boost in the recent years. The popularity of PEVs would also remarkably reduce the penetration of internal combustion engine based vehicles so as to reduce the fossil fuel cost and GHG emission. However, the new participants of charging demand would deteriorate the current intractable power system scheduling tasks, and would therefore cause the allocation problems of distributed energy resources [10].

### 68 1.2. State of the art

69 Due to the considerable complexity, constraints and binary switching effect of the power system [11], unit commitment (UC), a key issue in power system scheduling, is widely regarded as an NP hard problem [12] with strong

117 nonlinear, large-scale, mixed integer and high dimension174  
 118 features, where many attempts have been made for solv-175  
 119 ing the intractable problem. Existing conventional math-176  
 120 ematical based approaches, such as the dynamic program-177  
 121 ming [13], integer programming [14], mixed-integer pro-178  
 122 gramming [15, 16], branch and bound methods [17] and179  
 123 Lagrangian relaxation methods [18, 19], are able to achieve180  
 124 sufficient results given limited range problems, whereas181  
 125 they are prone to encounter dimension disasters under high182  
 126 complexity and large scale scenarios. With the fast devel-183  
 127 opment of the meta-heuristic algorithms (MA), their ad-184  
 128 vantages in problem modeling flexibility and searching effi-185  
 129 ciency have proved to be sufficient for solving UC problem186  
 130 [20, 21]. Popular MAs have been utilized including genetic187  
 131 algorithms (GAs) [20, 22], simulated annealing algorithm188  
 132 (SA) [23, 18], particle swarm optimization (PSO) [24],189  
 133 ant colony optimization (ACO) [25] and teaching learn-190  
 134 ing based optimization (TLBO) [26] and etc. In addition,191  
 135 specific variants of popular MAs have also been applied192  
 136 to the UC problem, such as binary particle swarm opti-193  
 137 mization (BPSO) [27], quantum-inspired particle swarm194  
 138 optimization (QPSO) [28] and hybrid particle swarm op-195  
 139 timization (HPSO) [29] etc. Though numerous methods196  
 140 have been proposed, the optimal solutions for high dimen-197  
 141 sional UC problems have not been obtained yet, adding198  
 142 that the emergence of large penetration of PEVs would199  
 143 address new difficulties to the system. 200

144 Driven by policy stimulus and rapid progress in science201  
 145 and technology, PEVs have been rapidly popularized. On202  
 146 one hand, PEVs would be potential to bring considerable203  
 147 benefits to the environment and economy. On the other204  
 148 hand, their large quantity power demand and stochastic205  
 149 charging behaviors would impose significant impact on206  
 150 the power systems [30, 31]. In addition, due to gradual207  
 151 expansion of the unit scale as well as the high degree of208  
 152 non-linearity and coupling characteristics, the optimal eco-209  
 153 nomic operation and coordination for the power system210  
 154 and PEVs have become extremely challenging [32, 33].  
 155 Therefore, intelligent scheduling for power units and PEV211  
 156 is an inevitable and arduous task, where numerous com-212  
 157 putational methods have been proposed [34, 35, 36, 37].213  
 158 Saber et al. [38, 39] proposed PSO based cost and emis-214  
 159 sion reduction in a smart grid by utilization of grid ve-215  
 160 hicles and renewable energy sources. Talebizadeh et al.216  
 161 [40] explored the economic impacts of PEV charging and217  
 162 discharging in the UC problem using GA and differential218  
 163 evolution (DE) methods. Yang et al. [41, 21] proposed219  
 164 BPSO based hybrid meta-heuristic methods for solving220  
 165 hybrid UC problem considering intelligent scheduling of221  
 166 PEVs. Jian et al. [42] proposed the valley filling algo-222  
 167 rithm for PEVs aggregators. ARIMA-based methods and223  
 168 game theory were employed to forecast the PEVs loads224  
 169 and optimize charging cost [43, 44, 45]. Multi-objective225  
 170 approaches [46, 47, 48, 49] have also been proposed to si-226  
 171 multaneously minimize the emission and economic costs of227  
 172 power unit and PEVs in power system. The majority of228  
 173 existing methods consider the PEVs as an aggregator and229

scheduling the charging and discharging under fully co-  
 ordinated or uncoordinated scenarios. However, very few  
 studied have considered the impact of different scales of  
 PEVs charging load coordinated with demand side man-  
 agement strategies on the UC economic cost.

The competitive swarm optimizer (CSO) algorithm was  
 proposed by Cheng and Jin in 2015 [50]. It was inspired  
 by the PSO algorithm and aims to improve the exploita-  
 tion ability of its ancestor. The CSO method gets ride  
 of the global and local optimums in PSO and adopts a  
 novel learning mechanism to generate a competition be-  
 tween particle pairs, where the losers should update their  
 velocity and position by learning from the winners. It is  
 found by comprehensive numerical studies that the perfor-  
 mance of convergence speed and result accuracy is signifi-  
 cant, particularly in solving large scale problems [51]. Re-  
 cent studies about the CSO algorithm can be divided into  
 two aspects, e.g. the development of algorithm variants  
 and applications to the engineer problems. Several vari-  
 ants of CSO algorithm, for example, modified competitive  
 swarm optimizer (MCSO) [52], orthogonal learning com-  
 petitive swarm optimizer (OLCSO) [53], dynamic com-  
 petitive swarm optimizer (DCSO) [54] and improved com-  
 petitive particle swarm optimizer (ICSO) [55] have been pro-  
 posed to effectively solve the economic dispatch, multiple  
 distributed generation (DG) unit [56] and other large-scale  
 power system optimization problem.

The majority of aforementioned studies, both from the  
 algorithms and system modeling sides, only considered the  
 UC problem and/or fixed demand side demand load ac-  
 cessed to the power system. However, very few studies  
 have been addressed on evaluation the economic impact  
 of different level of demand side load associating with the  
 optimal scheduling with unit commitment. The simultaneous  
 optimization of unit commitment and the flexible demand  
 side management for PEVs would of significant potential  
 in reducing the economic cost.

### 1.3. Contribution

In this paper, a parallel algorithm framework for si-  
 multaneously solving coordinate unit commitment and de-  
 mand side management of plug-in electric vehicles is pro-  
 posed, named as the PDUC problem. A real-valued com-  
 petitive swarm optimization method is used to optimize  
 the demand side load flexible access to power system, ad-  
 just the unordered charging load and decrease the load  
 of power system during the peak period. The unit sta-  
 tus is only scheduled using a binary algorithm because  
 of its unique binary switching and large-scale characteris-  
 tic. Therefore, a binary competitive swarm optimizer has  
 been improved based on the CSO algorithm for optimiz-  
 ing states. Then in the process of parallel optimization, a  
 weighting factor  $w$  was introduced in the PDUC problem,  
 in order to analysis the impact of demand side load with  
 different levels on the system. To this end, the numer-  
 ical experiments has been conducted to prove the feasibil-  
 ity and effectiveness of proposed algorithm framework for

solving the proposed PDUC problem. The major contributions of the paper are shown as below:

- A novel PDUC problem model is established simultaneously considering the optimal scheduling of unit commitment and demand side management of plug-in electric vehicles, where the unit state and flexible demand side load associated with multiple constraints were merged in the model.
- To solve the proposed PDUC problem, a brand new parallel optimization framework is established where a binary/real-valued competitive swarm optimizer is proposed and embedded in the framework to optimally allocate the generation unit as well as the demand side management of plug-in electric vehicles.
- A weighting factor  $w$  of the uncontrollable PEVs load was designed in the PDUC model, through which the impact of different levels of demand side management of plug-in electric vehicles on the economic cost has been extensively studied.

#### 1.4. Organization of the paper

The rest of the paper is structured as follows: The UC problem combined with plug-in electric vehicles formulation is presented in Section 2. The proposed parallel BCSO/CSO algorithm is given in the Section 3, followed by the detailed process demonstration of the proposed method for solving the UC problem and DSM of PEVs in Section 4. The experimental results and numerical analysis are presented in Section 5. Finally, Section 6 summarizes the article.

## 2. PDUC problem formulation

Continuous development of global economy calls for considerable increase of electric power demand and witnesses the significant growth of fossil fuel cost of power generation, particular in those coal dominated countries. Therefore, it is crucial to effectively solve the optimization problem of the unit commitment [57], which reduces huge economic expenses, fuel consumptions and the pollutant emissions. In addition, due to the dramatically increasing penetration of PEVs, new challenges would be brought into the power grid in terms of economic and secure factors. It is therefore a significant task to consider the optimal DSM of PEVs along with the unit commitment. In this paper, we simultaneously consider the optimal coordination of DSM of PEVs and traditional UC problem, namely PDUC problem. The objective function is to minimize the total economic cost of units in one day 24-hour time horizon, whereas the constraints consider PEVs sector in both original UC limits and novel PEVs management limits.

### 2.1. Objective function

The objective function of the UC system is the total economic cost during 24 hours, and an accumulation of two major parts of the objective function is shown in (1) as below.

$$TPC_{T_n} = \min \sum_{t=1}^T \sum_{j=1}^n [F_j(P_{j,t})u_{j,t} + SU_{j,t}(1 - u_{j,t-1})u_{j,t}] \quad (1)$$

The objective function consists of two components: the fuel economic cost and the start-up cost of units, where  $TPC_{T_n}$  represents the total economic cost to be optimized.  $u_{j,t}$  is the binary decision variable denoting the status of  $j^{th}$  unit at the  $t$  hour.  $F_j(P_{j,t})$  is the fuel cost of the  $j^{th}$  unit, in which generation output is represented as  $P_{j,t}$ . Besides the fuel cost in normal conditions,  $SU_{j,t}$  represents the star-up cost of the unit  $j^{th}$  during the  $t$  time.

#### 2.1.1. Fuel cost

The normal fuel cost function is modeled in a quadratic polynomial formation, which can be described by (2) shown as below,

$$F_{j,t}(P_{j,t}) = a_j + b_j P_{j,t} + c_j P_{j,t}^2 \quad (2)$$

where the  $a_j$ ,  $b_j$  and  $c_j$  are the fuel cost coefficients.

#### 2.1.2. Start-up cost

Given the commitment requests, the majority of power unit may be required to adjustments the operation status, e.g. to start up or turn down. The start-up units cost more fuel to initialize the conditions, due to which it is an indispensable part to be considered in the economic cost. The start-up cost is described as in (3),

$$SU_{j,t} = \begin{cases} SU_{H,j}, & \text{if } MDT_j \leq TOFF_{j,t} \leq MDT_j + T_{cold,j} \\ SU_{C,j}, & \text{if } TOFF_{j,t} > MDT_j + T_{cold,j} \end{cases} \quad (3)$$

According to the previous running condition and current on/off status of the unit, the start-up cost could be divided as the hot start and cold start costs. Let  $TOFF_{j,t}$  represent the continuous time of the  $j^{th}$  unit within off status. If  $TOFF_{j,t}$  is less than the cold start boundary  $T_{cold,j}$ , the start-up cost is considered as the hot start cost denoted as  $SU_{H,j}$ . Otherwise, the start-up cost of  $j^{th}$  unit belongs to a cold start  $SU_{C,j}$ . It should also be noted that  $MDT_j$  denotes the minimum down time of  $j^{th}$  unit and provides a lower boundary for the  $TOFF_{j,t}$ .

### 2.2. Constraints of PDUC problem

When the large-scale PEVs are connected to the electric power system, the uncoordinated charging profiles and significant load demand may easily cause overloading in distributed networks, which will bring unavoidable impact

305 to the system stable operation. In order to achieve the 334  
 306 optimal objective function and ensure the secure and eco-  
 307 nomic operation of the system, various equality and in-  
 308 equality constraints of the units and PEVs, for example  
 309 the power demand limit and charging bound limit, should  
 310 be considered.

### 311 2.2.1. Power balance constraint

The power balance constraint aims to maintain the bal-  
 ance between the power supply and demand in any time  
 slots. It is modeled as an equality constraint shown in (4),

$$\sum_{j=1}^n P_{j,t} u_{j,t} = P_{D,t} + P_{PEVload,t} + P_{PEV,t} \quad (4)$$

312 where  $P_{j,t}$  represents the generation output of  $j^{th}$  unit,  
 313 and  $P_{D,t}$  is the power demand at time  $t$  for the system.  
 314 Moreover,  $P_{PEVload,t}$  is the uncoordinated charging load  
 315 of PEVs aggregator at time  $t$  which is fully stochastic de-  
 316 pending on the users behaviors [58].  $P_{PEV,t}$ , on the other  
 317 hand, is the DSM of PEVs at time  $t$ . This controllable  
 318 load is a separate part and will be determined in the op-  
 319 timization process. The both types of PEVs act as extra  
 320 load demand which should be met by the power supply.

### 321 2.2.2. Generation limit constraint

The generation limit constraint of the unit is an in-  
 equality constraint which limits the power output of units  
 according to the corresponding physical capacity. It is  
 shown in the following equation (5):

$$u_{j,t} P_{j,min} \leq P_{j,t} \leq u_{j,t} P_{j,max} \quad (5)$$

322 where  $P_{j,min}$  and  $P_{j,max}$  represent minimum and max-340  
 323 imum power capacity respectively, while the generation341  
 324 output of  $j^{th}$  unit should be within the unit contribution342  
 325 boundaries.

### 326 2.2.3. Minimum up/down time limit constraint

The status of units only have binary options: '1' rep-  
 represents that the unit is on-line and '0' denotes an off-line  
 status, and the both status are related to the minimum  
 up/down time. The minimum up/down time constraints  
 is shown in (6),

$$u_{j,t} = \begin{cases} 1, & \text{if } 1 \leq TON_{j,t-1} < MUT_j \\ 0, & \text{if } 1 \leq TOFF_{j,t-1} < MDT_j \\ 0 \text{ or } 1, & \text{otherwise} \end{cases} \quad (6)$$

327 In this constraint, if the  $TON_{j,t-1}$  is less than minimum  
 328 up time of the  $j^{th}$  unit in the  $t-1$ , the  $j^{th}$  unit should  
 329 be kept on-line in the next hour  $t$ . Similarly, if the close  
 330 time of  $j^{th}$  unit does not reach the minimum down time,  
 331 it cannot be started up in the next hour, where  $TON_{j,t-1}$   
 332 and  $TOFF_{j,t-1}$  denote the continuous on-line or off-line  
 333 time by the slot  $t-1$ .

### 2.2.4. Spinning reserve limit constraint

The spinning reserve limit constraint is an inequality  
 constraint. Due to that the load demand of power system  
 is a predictive value, the spinning reserve provided from  
 the power suppliers is mainly to reserve enough potential  
 power contributions in dealing with the unexpected power  
 demand and effectively achieving the power balance. In  
 another word, it is to make sure the generation output  
 power of units exceed the sum of all types of load demand  
 in the actual system. The constraint is shown in (7):

$$P_{D,t} + P_{PEVload,t} + P_{PEV,t} + SR_t \leq \sum_{j=1}^n P_{j,max} u_{j,t}. \quad (7)$$

where  $SR_t$  represents the spinning reserves at time  $t$ , and  
 it is related to load demand of the power system. The  
 relationship of them can be described by the equation (8),  
 where  $m$  is the ratio coefficient and set as 0.1 [27] in this  
 paper.

$$SR_t = m \times P_{D,t}. \quad (8)$$

### 2.2.5. PEVs charging power limit

The PEVs aggregator obtain the power from the grid  
 subject to the charging capacity constraints which is shown  
 in (9),

$$P_{PEV,t,min} \leq P_{PEV,t} \leq P_{PEV,t,max}. \quad (9)$$

where the  $P_{PEV,t,min}$  denotes the minimum charging power  
 of PEVs at time  $t$ , and  $P_{PEV,t,max}$  is the maximum bound-  
 ary restriction. The both boundaries largely depend on the  
 number of PEV aggregation and the capacity of each par-  
 ticipants. The constraint rule should be followed in the  
 DSM of PEVs and the boundary is determined according  
 to the actual charging data of PEVs.

### 2.2.6. PEVs power demand limit

Another constraint of PEVs is the power demand limit.  
 It requires that the sum of charging power should be equal  
 to the necessary charging power, which is the bottom line  
 of PEVs to supply the daily commute. The PEVs power  
 demand limit is shown in (10):

$$\sum_{t=1}^T P_{PEV,t} + \sum_{t=1}^T P_{PEVload,t} = P_{PEV,total}. \quad (10)$$

where the  $P_{PEV,t}$  denotes the DSM of PEVs at time  $t$ ,  
 $P_{PEV,total}$  is total necessary charging power and  $P_{PEVload,t}$   
 is uncoordinated charging load at time  $t$ . The value of  
 $P_{PEVload,t}$  is closely related to the weight factor of PEVs  
 charging load, which is defined as  $w$  and shown in the  
 equation (11):

$$w = \frac{\sum_{t=1}^T P_{PEVload,t}}{P_{PEV,total}} = \frac{P_{PEV,total} - \sum_{t=1}^T P_{PEV,t}}{P_{PEV,total}} \quad (11)$$

The specific settings of the parameters such as  $P_{D,t}$ ,  $MUT_j$  and  $MDT_j$  highly depend on the test system and are shown in the table 1. All constraints handling techniques will be elaborated in the Section 4.

### 3. Binary/real-valued competitive swarm optimization

The characteristics of the proposed PDUC problem, with largely access of significant PEVs load, has been a multi-modal, highly dimensional, strong non-linear and highly complex optimization task. The status of units are binary variables whereas the power output and DSM of PEVs are real-valued ones. This leads to a mixed integer decision variables formulation which remarkably challenges the conventional optimization tools. In this paper, a novel parallel meta-heuristic algorithm is proposed combining real-valued and binary CSO algorithms to solve the proposed PDUC problem. The binary competitive swarm optimizer algorithm is inspired from discrete PSO algorithm and it is specialized in solving the PDUC problems with high dimensionality, taking the advantage of CSO evolutionary logic [50].

#### 3.1. Competitive swarm optimization

The CSO algorithm is inspired from particle swarm optimization, while the idea and evolutionary process are unique. The particles of PSO update their velocities and positions considered as the social and self cognition learning based on the featured particles  $p_{best}$  and  $g_{best}$ , both of which indicate the best position of each particle in the corresponding track and the global best position respectively [59]. Unsurprisingly in the CSO algorithm design, the parameters  $g_{best}$  and  $p_{best}$  have been removed, and a pairwise competition mechanism between the particles has been introduced. The competitive mechanism process of CSO is show in Figure 1.

It could be observed in Figure 1 that two particles in the population  $P_t$  will be selected and competed with each other along with the iterations. Loser and winner particles are produced in the process of competition, where the fitness function values of losers are larger (in minimization problems) than that of the winners. Therefore, the loser particles and should update their velocity and position by learning from the winners. Then, the winners and updated losers are put into the  $P_{t+1}$  to generate the new population of the next iteration. In the iteration process,  $P_t$  denotes the whole particle swarm at current iteration  $t$ . The number of particles is  $N$ , and  $P_t$  is expressed as  $P_t = (x_{(1)}, x_{(2)}, \dots, x_{(n)})$ . Suppose the dimension of particle is  $n$ , the positions of these particles are denoted by  $X_i(t) = (x_{(i,1)}(t), x_{(i,2)}(t), \dots, x_{(i,n)}(t))$ , and the velocity of these corresponding particles is denoted by  $V_i(t) = (v_{(i,1)}(t), v_{(i,2)}(t), \dots, v_{(i,n)}(t))$ . In each generation, the swarm  $P_t$  is randomly divided into  $N/2$  couples, and hence there will be  $N/2$  times competitions in each generation. In the competition, the fitness of these particles

are compared and the whole population are divided into a winner group and a loser group. In the  $k^{th}$  competition of the  $t^{th}$  iteration, the losers update their positions and velocities by learning from the winners as shown in (12) and (13) respectively:

$$V_{l,k}(t+1) = R_1(k,t)V_{l,k}(t) + R_2(k,t)(X_{w,k}(t) - X_{l,k}(t)) + \phi R_3(k,t)(X'_k(t) - X_{l,k}(t)). \quad (12)$$

$$X_{l,k}(t+1) = X_{l,k}(t) + V_{l,k}(t+1). \quad (13)$$

where  $X_{w,k}(t)$  and  $X_{l,k}(t)$  represent the position of winners and losers respectively, and the velocity is denoted by  $V_{l,k}(t)$ , with  $k = 1, 2, \dots, m/2$ .  $R_1(k,t)$ ,  $R_2(k,t)$  and  $R_3(k,t)$  are the random numbers in the generation  $t$  ranging between 0 and 1. The  $X'_k(t)$  is the mean position value of the whole swarm particle  $P_t$ . The  $\phi$  is the only parameter to be tuned in the algorithm, and it can control the influence of  $X'_k(t)$  in the optimization process.

In each iteration, every particle has only one chance to take part in the competition, and after the competition the winner will be directly put into the swarm  $P_{t+1}$  for the next generation. The loser will be thrown into swarm  $P_{t+1}$  after the update of velocity and position. The tuning parameter of this algorithm sees only one to be determined. Comparing to the three parameters in PSO, CSO method significantly reduces the tuning efforts and improves the algorithm efficiency and adaptability. In this paper, canonical CSO method is directly adopted together with a novel proposed binary variant to simultaneously optimize unit commitment and the DSM of PEVs.

#### 3.2. Binary CSO

In many practical high dimensional decimal optimization problems, the CSO algorithm has been successfully applied and obtained competitive results. However, a large number of real world problems have integral variables and require discrete algorithms. In this paper, a novel binary CSO algorithm is proposed and its algorithm principle is shown in Figure 2. The BCSO algorithm is improved based on the CSO algorithm. In order to distinguish the position value of particles in the decimal CSO algorithm,  $X_{b,k}(t)$  is defined as the binary variables to represent the start-up and shut-down status of units. In the process of competition, the  $X_{b,w,k}(t)$  and  $X_{b,l,k}(t)$  denote the binary winner particles and loser particles respectively. The binary decision variables of loser particles update according to a transfer function from the updated velocity, where a V-shape transfer function is adopted as shown in (14) and (15).

$$V_{l,k}(t+1) = R_1(k,t)V_{l,k}(t) + R_2(k,t)(X_{b,w,k}(t) - X_{b,l,k}(t)) + \phi R_3(k,t)(X'_{b,k}(t) - X_{b,l,k}(t)). \quad (14)$$

$$S(V_{l,k}) = 2 \times \left| \frac{1}{(1 + \exp(-V_{l,k}(t+1)))} - 0.5 \right|. \quad (15)$$

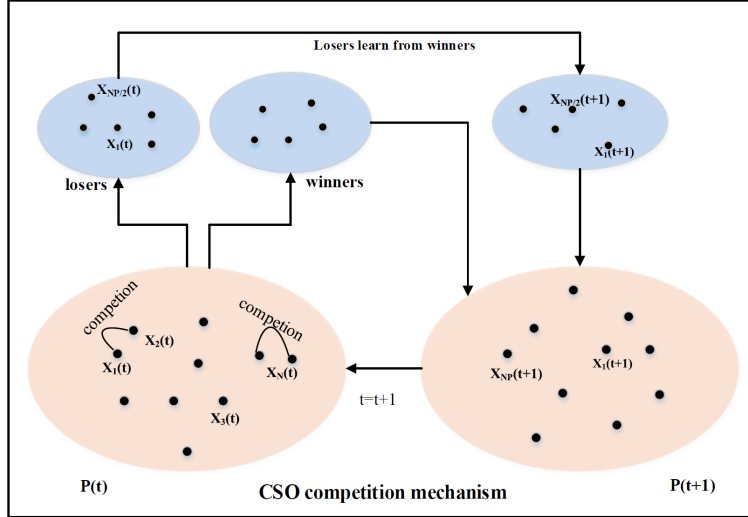


Figure 1: The competitive mechanism of CSO algorithm

where the velocity  $V_{l,k}(t+1)$  is the updated value of losers and it has a larger impact on  $S(V_{l,k})$ . Therefore, the velocity  $V_{l,k}(t+1)$  or  $V_{w,k}(t)$  will be limited to a certain range of  $[-4,4]$ .  $S(V_{l,k})$  is a proportional value related to the value of  $V_l(t+1)$ , and it determines the 0 or 1 status of the binary variables according to (16).

Next, the value of binary particles will be determined according to (16), where the proportional value  $S(V_{i,j})$  is obtained by (15).

$$X_{b,l,k}(t+1) = \begin{cases} 1, & \text{if } rand < S(V_{l,k}) \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

$X_{b,l,k}(t+1)$  represents the binary loser particle, and the  $rand$  in (16) is a uniformly distributed random number among  $(0,1)$ . If the  $S(V_{l,k})$  is greater than  $rand$ , the value of particle is 1 and vice versa. The proposed BCSO method will be running parallel with the real-valued algorithm to solve the PDUC problem, and the detailed parallel algorithm procedure will be illustrated in the next section.

#### 4. Proposed parallel algorithm structure

The DSM of PEVs has been a novel and important issue given potential negative impact to the power grid due to the unexpected charging spikes from PEVs. This coordinated problem has also been a significantly challenging task when combined with the intractable UC problem to realize economic cost minimization. In this paper, the binary and real-valued competitive swarm optimizations have been parallel organized for solving the PDUC optimization problem. The integral optimization process is shown in Figure 3.

It can be seen from Figure 3 that the process of completed system consists of two separate parts: the binary

optimization process is for updating the units status and the real-valued optimization is for determining the intelligent DSM of PEVs. The mixed coding structure of a population for the proposed parallel optimization algorithm is shown in Figure 4. To explore the effect of different scale for DSM of PEVs loads on the power system, it is necessary to distribute the actual charging load of the PEVs according to the certain ratio before optimizing the DSM of PEVs. Moreover, various constraints are required to be handled. The detailed procedure of the optimization is given below. 1) *Distribution of the load factor* :

In the first instance, the actual charging data of the PEVs of a city in a 24-hour time horizon should be imported. To validate the impact of different degree of disorder charging strategy and intelligent scheduling for DSM of PEVs on power system respectively, the proportion between the coordinated or uncoordinated PEVs load should be preset. One part is regarded as the uncontrolled load which is combined with the overall power load demand as shown in (4), and the other part is used to schedule by the proposed BCSO/CSO algorithm.

##### 2) Initialization :

The process of initialization includes power system data, PEVs data, as well as corresponding parameters in power system such as the coefficients of fuel, maximum/minimum generation output, hot/cold start cost, minimum up/down time and initial status of units. It is also necessary to set the velocity range of particles and parameters in the algorithm.

##### 3) Constraints processing :

To handle the constraint conditions is another indispensable step. From Figure 3, it can be observed that the initialized solution of units should satisfy the minimum up/down time limit. Otherwise, the status should be modified according to the limited range. In addition, the PEVs charging constraints (9) and (10) should also be

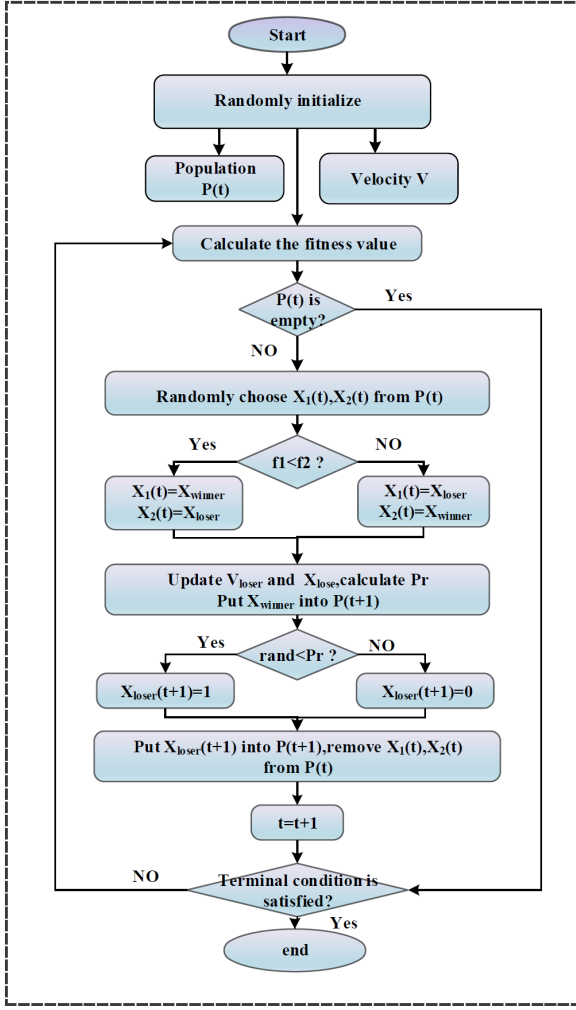


Figure 2: The principle diagram of BCSO algorithm

At last, the evolutionary update terminates until reaching the maximum iteration number. If not, go back to step 3).

## 5. Results and analysis

In this section, comprehensive scenario analysis of PDUC problem has been investigated to validate the effectiveness of the novel proposed algorithm and the impact on the economic cost. The different scenarios are shown in Figure 5, which includes the UC without PEVs charging load, with various uncoordinated PEVs load, and with DSM of PEVs charging load. The 10 unit benchmark system has been adopted and the data is shown in table 1 [20]. In order to truly reflect the actual charging demand of PEVs, the one day real charging data in Shenzhen, China has been collected and the charging curve is showed in figure 6. It can be seen from the curve that the off-peak charging period is between 8:00-10:00 and 16:30-17:50, and the peak of charging is between 1:00-4:00 and 12:30-14:00. This practical data demonstrates the charging behaviors of PEVs users, and the total charging load is 501.40MW for a single day. Such uncoordinated charging behaviors will have a significant impact on the load of power system. According to the actual data of different charging locations in Shenzhen, it could be found that most PEVs users would like to charge immediately in charging stations, of which the charging time is more random and the load is uncontrollable. On the other hand, in the places of household and parking lot, the owners can arrange the charging time freely, where the coordinated charging might be realistic. In this regard, a weighting factor  $w$  is introduced as in (11) to distribute total charging load into two categories: the uncoordinated load of charging station and the coordinated demand side management load of household and parking lot, which is shown in Figure 5.

Effective experimental results heavily depend on the choice of parameters in the algorithm. Therefore, the only algorithm parameter  $\phi$  of CSO/BCSO has been well tuned and presented in the first half of table 3. The second part of table 3 showed the tuning process of the weighting factor  $w_{BPSO}$  of BPSO algorithm. The tuning range of  $\phi$  is from 0.0 to 0.3 with the step as 0.05. The learning factor  $C1, C2$  in BPSO are set as the fixed valued 2 [24], and the range of weighting factor is adjusted from 0.60 to 0.75 with 0.05 step. From the table 3 it could be found that 0.10 was chosen as the value of  $\phi$  under the 10 unit benchmark test, and the  $w_{BPSO}$  of BPSO is adopted as 0.75, and the parameter settings for the algorithms have been fixed for all the numerical studies. Three different scenarios are chosen for analysis and discussion. In the Case 1, BCSO is applied to optimize the 10 unit benchmark UC problem with the association of lambda iteration method, and no PEVs are considered. The algorithm process can be found in the left half of Figure 3 and this case aims to validate the effectiveness of BCSO algorithm; Then Case 2 compares the optimization results of PDUC problem under different unit

met. Then, the spinning reserve constraints (7) is handled with the newly updated status with the scheduled and unscheduled PEVs load.

### 4) Economic load dispatch :

In this step, the total economic cost is calculated using (1) with the states of units obtained from the above steps, and the lambda iteration method is employed to solve the economic load dispatch. The range of generation output power is also checked according to the constraints (5) and (4).

### 5) Evolutionary update :

In order to find the optimal solutions to the objective function, BCSO and CSO methods are applied to update the variables in the system according to the obtained results of fitness function from step 4). The process is running parallel including the binary optimization updated by BCSO and real-value CSO optimization for DSM of PEVs. The corresponding speeds of particles are evolutionarily updated at the same time.

### 6) Judging iteration conditions :



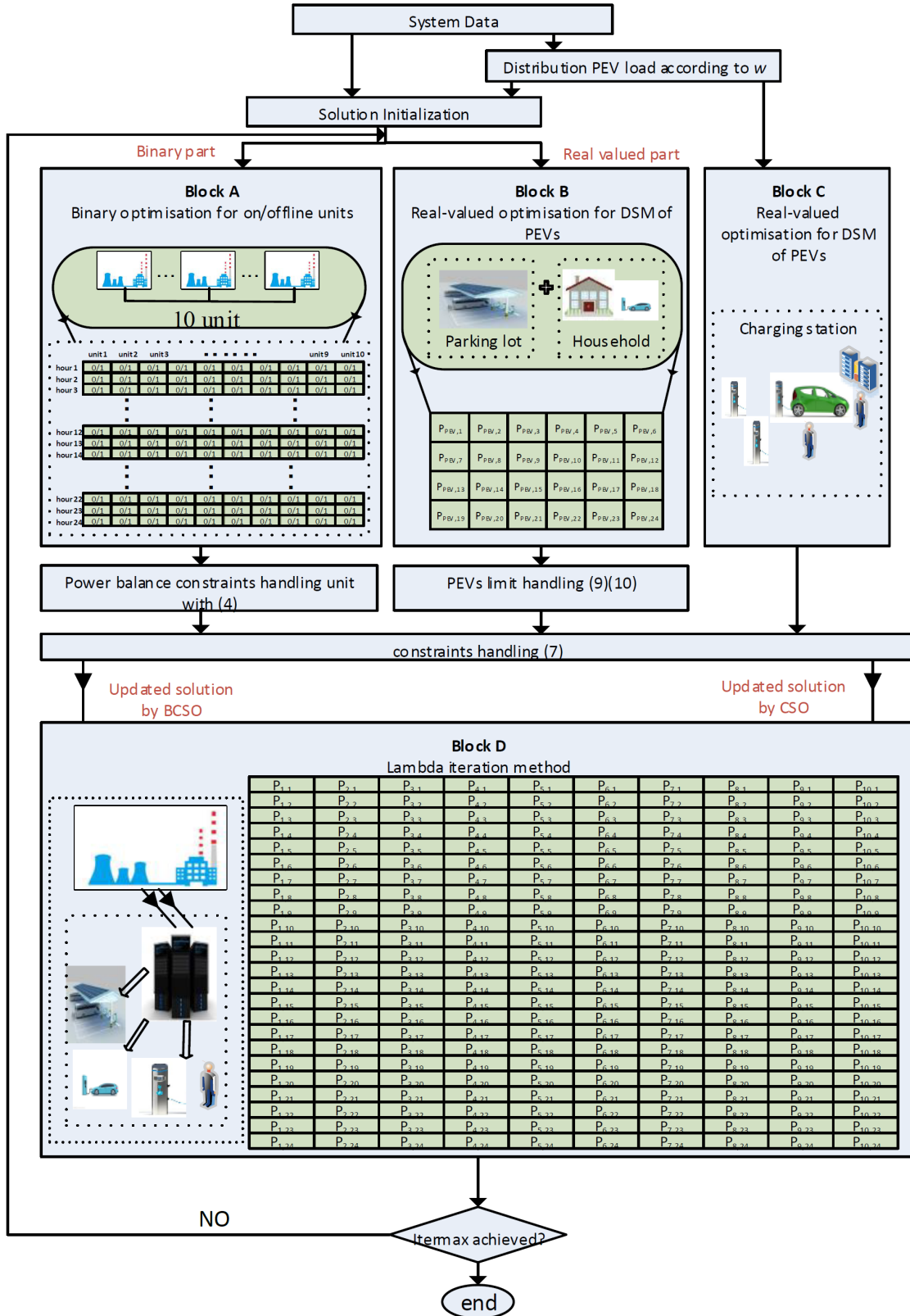


Figure 3: The schematic of proposed method for solving the PDUC problem

537 scales ranging from 10-100 with the integration of several  
 538 levels of uncoordinated charging of PEVs, demonstrating  
 539 the competitive performance of the proposed BCSO for

solving PDUC problem. At last in Case 3, comprehensively comparative studies has been conducted on PDUC problem considering the economic impact of multiple dif-

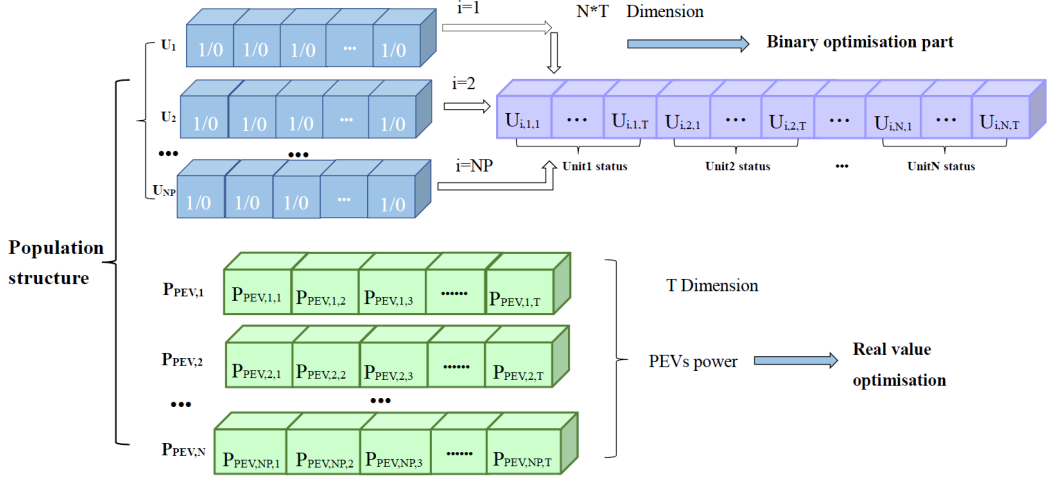


Figure 4: Structure of a population for the proposed parallel optimization algorithm

Table 1: Unit commitment data setting for BCSO

	Unit1	Unit2	Unit3	Unit4	Unit5	Unit6	Unit7	Unit8	Unit9	Unit10
Pmax(MW)	455	455	130	130	162	80	85	55	55	55
Pmin(MW)	150	150	20	20	25	20	25	10	10	10
a(\$ /h)	1000	970	700	680	450	370	480	660	665	670
b(\$ /h)	16.19	17.26	16.6	16.5	19.7	22.26	27.74	25.92	27.27	27.79
c(\$ /h <sup>2</sup> )	0.00048	0.00031	0.002	0.00211	0.00398	0.00712	0.00079	0.00413	0.00222	0.00173
MUT(h)	8	8	5	5	6	3	3	1	1	1
MDT(h)	8	8	5	5	6	3	3	1	1	1
$SU_H$ (\$)	4500	5000	550	560	900	170	260	30	30	30
$SU_C$ (\$)	9000	10000	1100	1120	1800	340	520	60	60	60
$T_{cold}(h)$	5	5	4	4	4	2	2	0	0	0
Initial Status(h)	1	1	0	0	0	0	0	0	0	0

ferent proportions of PEVs charging load of uncoordinated  
and DSM of PEVs, and Figure 5 shows the process.

### 5.1. Case 1: 10 units benchmark solved by BCSO

In this case, only conventional UC problem of 10 unit  
benchmark is considered and solved by the novel proposed  
BCSO problem. The spinning reserve is set as 10%, and  
30 independent runs have been conducted to eliminate the  
randomness. To fairly compare the results with counter-  
part solvers, the particle number of BCSO population is set  
to 150, and the maximum number of iteration is 200, seeing  
similar function evaluations with previous approaches [60].  
State-of-the-art algorithms including IBPSO [60], IPSO  
[61], HPSO [29], QBPSO [62], SA [63], brGA [64], DBDE  
[65], BGSO [66] and BPSO series [41] have been compared  
under the same benchmark and the results are shown in  
the table 2. The figure 7 shown the average evolutionary  
results of BCSO, BPSO, BLPSO and NBPSO. It could  
be found from the table 2 that the best and worst val-  
ues of BCSO are both the optimal value 563937.68 \$/day  
with the standard deviation being as 0.00. The excellent

result shows significantly advantages comparing with all  
other counterpart algorithms and the remarkable stabil-  
ity of BCSO for solving the UC problems. In terms of  
the CPU cost time, BCSO has also shown comparatively  
shorter time span. From Figure 7, it could be found that  
the BCSO result in green curve has the best convergence  
speed and lowest optimal value, and the algorithm can  
find the optimal solution within only 15 iterations. It can  
be concluded that the proposed BCSO algorithm is fully  
capable in solving the UC problem and it can bring signif-  
icant economic benefits.

### 5.2. Case 2: PDUC problem with different unit scales and PEV load levels

With the continuous increase of PEVs number, the  
charging load scale of PEVs has become an important is-  
sue on the original power demand load in the system. In  
this section, the PDUC problem with different unit scales  
and PEV load levels are comparatively studied. The sub-  
case C2-S1 aims to compare the different unit scales with  
fixed PEVs charging load, whereas sub-cases C2-S2 and

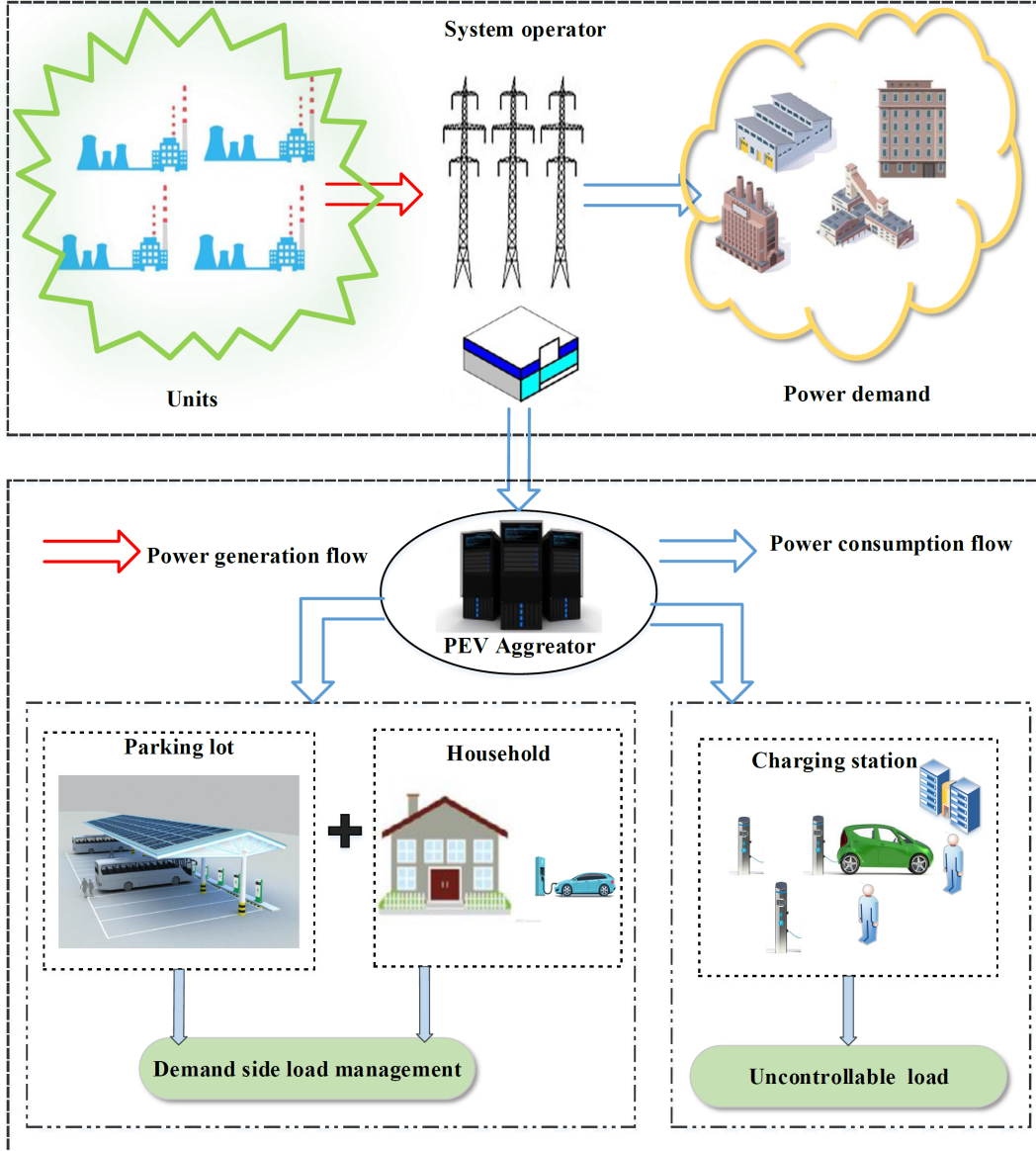


Figure 5: Three categories of PEVs load

583 C2-S3 compare the 10 unit benchmark with various PEV<sub>S598</sub>  
 584 uncontrollable load. The actual charging load of PEVs in<sub>S599</sub>  
 585 a Shenzhen city during 24-hour one day time horizon has<sub>S600</sub>  
 586 been integrated, which is shown in Figure 6. The PDUC<sub>S601</sub>  
 587 problem is optimized by the proposed BCSO algorithm<sub>S602</sub>  
 588 with the same algorithm parameter settings with Case 1,<sub>S603</sub>  
 589 and 10 independent runs are conducted for all the sub-<sub>S604</sub>  
 590 cases in Case 2 to eliminate the randomness. <sub>S605</sub>

591 *5.2.1. C2-S1: Different unit scales with fixed uncoordi-<sub>S607</sub>*  
 592 *ated charging load level* <sub>S608</sub>

593 In sub-case C2-S1, different unit scales have been adopted<sub>S604</sub>,  
 594 and a fixed PEVs uncoordinated charging load with a to-<sub>S610</sub>  
 595 tal of 501.40MW shown in figure 6 is integrated within the<sub>S611</sub>  
 596 multiple unit scales, including 10, 20, 40, 60, 80 and 100<sub>S612</sub>  
 597 units. The three BPSO variants including BPSO, NBPSO,

BLPSO [41] have been adopted in the algorithm compar-  
 ison. The experimental data and simulation curve of the  
 evolutionary process are shown in the table 4 and Figure  
 8 respectively.

From the table 4, it could be found that economic cost  
 optimized by BCSO is less than other algorithms, and the  
 differences dramatically increase with the unit numbers  
 increase. For example, when the unit number is 10, the  
 best fitness of BCSO is 576017.28 \$/day and 39.25 \$/day  
 less than the cost of BPSO, whereas the difference has in-  
 creased to 79627.61 \$/day when the unit number is up to  
 100. The worst value and standard deviation of BCSO  
 also achieve the lowest results in all unit scenarios. Fig-  
 ure 8 also proves the best performance of BCSO in solving  
 the given scenario. It could be observed from Figure 8

Table 2: Comparison between BCSO and other algorithms for 10 unit benchmark problem

Method	Cost(\$/day)							Std(\$)	Time(s)
	Trials	Population	Iteration	Best(\$)	Mean(\$)	Worst(\$)			
IBPSO [60]	10	20	2000	563777	564155	565312	143	27	
IPSO [61]	50	40	1000	563954	564162	564579	-	-	
HPSO [29]	100	20	1000	563942.3	564772.3	565785.3	-	-	
QBPSO [62]	50	-	1000	563977	563977	563977	0.00	18	
GA [20]	20	50	500	565825	-	570032	-	221	
SA [63]	-	-	50	565828	565988	566260	-	3.35	
brGA [64]	30	-	1000	563938	564253	564088	18	-	
DBDE [65]	20	40	1000	563977	564028	564241	103	3.6	
BDE	50	20	1000	563977	563977	563977	0.00	-	
BGSO [66]	50	50	-	563938	563952	564226	-	3	
BPSO [41]	30	150	200	563955.99	564000.40	564053.73	21.63	25.45	
BLPSO [41]	30	150	200	563977.01	563982.09	563987.16	-	22.09	
NBPSO [41]	30	150	200	563937.68	563962.59	563977.01	-	21.91	
BCSO	30	150	200	<b>563937.68</b>	<b>563937.68</b>	<b>563937.68</b>	0.00	11.58	

Table 3: Parameter tuning for BCSO and BPSO

C2-S1: PEV load=501.40MW									
Method	factor	unit=10				unit=100			
		Best(\$)	Mean(\$)	Worst(\$)	Time(s)	Best(\$)	Mean(\$)	Worst(\$)	Time(s)
BCSO	0.00	576017.28	576027.89	576059.12	16.80	5623579.42	5623759.33	5624002.85	89.22
	0.05	576017.28	576024.77	576027.98	16.70	5622827.26	5623657.88	5623937.34	107.13
	0.10	<b>576017.28</b>	<b>576022.63</b>	<b>576027.98</b>	<b>16.69</b>	5623157.05	5623533.45	5623801.62	106.18
	0.15	576017.28	576023.70	576027.98	16.69	5623272.82	5623501.42	5623747.96	100.73
	0.20	576017.28	576023.70	576027.98	16.95	5623386.39	5623603.58	5623789.29	89.81
	0.25	576017.28	576027.70	576030.12	16.65	<b>5622547.17</b>	<b>5623415.79</b>	<b>5623725.21</b>	<b>89.41</b>
	0.30	576017.28	576025.34	576028.93	16.70	5622592.12	5623283.94	5623853.92	87.36
BPSO	0.55	576131.40	576389.20	576632.69	14.43	5702133.89	5713199.33	5727424.49	63.73
	0.60	576097.33	576251.62	576544.83	15.09	5698724.15	5712761.20	5726925.54	67.14
	0.65	576069.27	576293.84	576527.49	14.74	5705885.02	5714677.18	5724431.61	77.46
$w_{BPSO}$	0.70	576059.12	576162.78	576517.34	15.53	<b>5697735.57</b>	<b>5712383.37</b>	<b>5729826.95</b>	<b>67.30</b>
	0.75	<b>576058.57</b>	<b>576163.24</b>	<b>576456.61</b>	<b>14.51</b>	5700470.92	5707459.36	5713368.27	77.32

that the BCSO shows quick converge speed, converging to the optimal value in 25 iterations. Although the NBPSO algorithm can converge at similar speed, the optimal economic cost is worse than BCSO algorithm. It should be noted that the optimal value and convergence speed of BCSO showing larger advantage as the dimension increase. This is majorly due to the strength of original CSO evolutionary logic, showing strong capability in escaping from local optimum for high dimensional problems. In terms of The CPU running time, BCSO is also less than the others. The better performance under difference unit scales proves that the BCSO algorithm is fully suitable for solving large scale PDUC problems.

### 5.2.2. C2-S2 and C2-S3: Different unit scales with various uncoordinated charging load levels

With the unprecedented penetrations of PEVs, the charging load level of PEVs will rapidly boost in the future years. To quantitatively evaluate the impact of uncoordinated charging load on the UC optimization results in power system, the actual uncoordinated charging load is scaled to different levels and evaluated under multiple unit scales to compare the economic result. Ten independent experiments were conducted for each scenario, under different units scales and load levels, the results are shown in the table 5. Three levels of PEVs uncoordinated charging loads, e.g. C2-S1 (the same with previous sub-case), C2-S2 and C2-S3, have been compared under unit scales again from 10 to 100, where the corresponding load values are 501.4MW, 807.81MW and 1002.80MW respectively. All

Table 4: Simulation results comparison between BCSO and BPSOs on C2-S1

C2-S1: PEV load=501.40MW						
Unit	Method	Cost(\$/day)			Time(s)	Std(\$)
		Best(\$)	Mean(\$)	Worst(\$)		
10	BCSO	576017.28	576022.63	576027.98	16.69	5.63
	BPSO	576056.53	576269.94	576577.93	19.98	218.68
	NBPSO	576053.56	576235.74	576544.84	19.30	208.91
	BLPSO	576027.98	576485.40	576733.30	18.86	219.72
20	BCSO	1136186.10	1136293.59	1136349.73	20.57	46.76
	BPSO	1137647.72	1138502.62	1139489.61	27.71	504.79
	NBPSO	1137399.85	1139318.82	1139904.90	27.95	715.81
	BLPSO	1142037.78	1143460.12	1145321.49	27.86	1294.09
40	BCSO	2257509.66	2257662.57	2257770.56	35.74	75.22
	BPSO	2276192.29	2281516.05	2288802.80	41.59	4126.14
	NBPSO	2274909.92	2284452.42	2289385.36	44.16	5076.65
	BLPSO	2280300.36	2287091.27	2296356.27	42.31	5199.00
60	BCSO	3379890.16	3380096.98	3380211.49	49.25	101.66
	BPSO	3408410.46	3415959.76	3423671.99	56.10	4558.29
	NBPSO	3407201.32	3415471.35	3419120.76	55.32	3401.93
	BLPSO	3415245.37	3423061.13	3431988.94	54.27	5114.40
80	BCSO	4501534.67	4501802.95	4501919.85	72.39	115.71
	BPSO	4550619.47	4563527.09	4574005.66	80.11	8100.67
	NBPSO	4548554.68	4560941.61	4569231.01	74.67	6524.02
	BLPSO	4564812.49	4573347.99	4585479.48	74.58	5588.36
100	BCSO	5622547.17	5623415.79	5623725.21	89.41	387.93
	BPSO	5702174.78	5710296.00	5723346.82	85.51	8132.28
	NBPSO	5704735.73	5720497.64	5728715.53	86.87	7196.53
	BLPSO	5695449.42	5711162.82	5726273.95	88.30	10299.95

the results are obtained by proposed BCSO method with the same parameter settings with C1. The figure 10 describes the evolutionary trend of best fitness.

It could be seen in the table 5 and figure 10 that the mean values of economic costs rise almost under the same proportion with the increase of unit scale. In addition, with the uncoordinated PEVs charging load increases, the best fitness and worst values increase at the same unit number sub-cases. More specifically, when the unit number is 10 in table 2, the economic cost is the smallest when the uncoordinated charging load is 501.4MW, and the difference between the optimal values of C2-S3 and C2-S1 is 13235 \$/day. Comparing with different load scales of C2-S1 under 10 unit power system which is shown in Figure 9, it could be observed that the propose BCSO method can quickly converge to the optimal value, although the number of iterations to reach best fitness is different.

According to the above experimental results and comprehensive analysis in Case 2, the proposed BCSO has proved to be effective in solving various scenarios of PDUC problem. The different levels of uncoordinated PEVs charging

load bring significant extra economic cost for unit commitment operation. Therefore, reasonable adjustment of charging load and unit status is more crucial for power system operators.

### 5.3. Case 3: PDUC problem with different unit scales and levels for DSM of PEVs

Both C1 and C2 only compare the fixed charging distribution of PEVs according to the real world profile shown in figure 5. In this case study C3, the flexible DSM of PEVs charging load will be considered, and the overall PEVs charging load of a 24-hour time horizon are separated as partly coordinated and uncoordinated loads. In order to explore the effects of coordinated/uncoordinated charging load in the power system, a PEVs charging factor  $w$  is defined as in (11) scaling the PEVs charging load type and flexibility. In this case C3, the unit number is 10 and charging amount is still 501.40 MW. The PEVs charging factor  $w$  is designed as the proportion of uncoordinated PEVs charging loads accounting for the overall PEVs load, and  $1 - w$  represents the coordinated rate of

Table 5: Simulation results comparison of various uncoordinated charging load levels

Unit	load	Cost(\$/day)			Time(s)	Std(\$)
		Best(\$)	Mean(\$)	Worst(\$)		
10	<i>C2-S1</i>	576017.28	576022.63	576027.98	16.69	5.63
	<i>C2-S2</i>	584176.14	584177.39	584177.52	13.59	0.43
	<i>C2-S3</i>	589252.28	589258.37	589283.42	13.96	12.83
20	<i>C2-S1</i>	1136186.10	1136293.59	1136349.73	20.57	46.76
	<i>C2-S2</i>	1143398.55	1143556.71	1143621.00	21.43	84.92
	<i>C2-S3</i>	1148340.50	1148552.35	1148637.91	21.44	105.65
40	<i>C2-S1</i>	2257509.66	2257662.57	2257770.56	35.74	75.22
	<i>C2-S2</i>	2265563.68	2265688.78	2265819.69	38.41	95.57
	<i>C2-S3</i>	2269609.74	2269678.78	2269808.96	38.12	66.19
60	<i>C2-S1</i>	3379890.16	3380096.98	3380211.49	49.25	101.66
	<i>C2-S2</i>	3386117.59	3386515.18	3386772.51	53.15	232.00
	<i>C2-S3</i>	3392267.85	3392557.10	3392794.96	51.91	184.81
80	<i>C2-S1</i>	4501534.67	4501802.95	4501919.85	72.39	115.71
	<i>C2-S2</i>	4508923.08	4509160.25	4509531.95	75.27	200.92
	<i>C2-S3</i>	4513643.06	4513890.08	4514169.02	73.32	169.97
100	<i>C2-S1</i>	5622547.17	5623415.79	5623725.21	89.41	387.93
	<i>C2-S2</i>	5630717.16	5631031.03	5631295.54	88.16	200.67
	<i>C2-S3</i>	5635524.41	5635709.56	5635858.33	89.42	98.71

charging load. When the  $w$  is  $1/3$ , it means the amount of DSM of PEVs over uncoordinated charging load ratio are 2:1, where 334.27 MW charging load is coordinately optimized and the other part is fixed power demand load. The weighting factor  $w$  is set to  $1/4$ ,  $1/3$ ,  $1/2$ ,  $2/3$ ,  $3/4$ ,  $4/5$  respectively in this case. The both BCSO and CSO methods are adopted for solving the PDUC problem where the parameters settings are the same to the previous cases. The experimental results of economic cost with different ratios are shown in Figure 11. Meanwhile, the mean values and cost times are shown in the table 8.

It can be seen from Figure 11 and Table 8 that the best and mean value of total economic cost significantly increases with the  $w$  decreases. Specifically, when the uncoordinated charging load accounts for  $1/4$  of the total charging load, the optimal value is 573144.46 \$/day. When the ratio increases to  $4/5$ , the best fitness is 575869.97\$, the difference is 2725.51\$, e.g. 0.4% cost has been effectively reduced by improving the proportion of coordinated load. Further, when compared with the no PEVs scenarios in table 4, this difference is even larger. The results prove that the optimal dispatching of DSM of PEVs charging load has significant effect in reducing the power system cost, and the scale of uncoordinated charging load should be reduced as much as possible.

The table 6 and 7 describe the accumulated optimal power demand of units and DSM of PEVs with  $w = 1$  and  $1/2$  respectively, where the PEV load is again 501.40 MW and the unit number is 10. Figure 12 shows the optimal

power demand curve considering the PEVs when  $w$  is 1,  $1/2$ , and 0. The optimal power contribution of each unit for the different  $w$  scenarios are shown in Figure 13. It could be observed from the table 6 and Figure 13 that the peak periods of the overall power demand are during the 10:00-13:00 and 20:00-21:30, while the periods 1:00-4:00, 12:00-14:00 and 19:00-20:00 and 21:00 are the peak charging time for the uncoordinated PEVs charging due to the behaviors of PEVs users. Such characteristics could be also observed from figure 6. This charging distribution may deteriorate the original peak demand such as 12:00 and 20:00 and is easy to cause power outages. The DSM of PEVs charging proposed in the paper could effectively relieve this problem. It could be observed from the table 7 that the peak of power load is not changed, whereas the maximum load has been transferred. For example, the charging peak has moved from 19:00-20:00 to 16:00-18:00. Therefore, though all the units are on-line in order to meet the power demand in the peak period, the power output of expensive units can be reduced by the intelligent demand shifting using proper algorithms.

Comparing the charging load curve with different scenarios in Figure 12, it could be observed that the peak value has decrease significantly, the first and second peak range of power load has a slight shift, and the valley values have obviously increased with the expansion of DSM for PEVs load. It proves that the optimal DSM of PEVs not only reduce the economic cost, but also achieve the effect of peak shifting and valley filling. Although the DSM of

Table 6: Best solution of C3 with PEVs charging factor  $w = 1$ 

Hour	W=1										Demand(MW)	PEV load(MW)
	U1(MW))	U2(MW)	U3(MW)	U4(MW)	U5(MW)	U6(MW)	U7(MW)	U8(MW)	U9(MW)	U10(MW)		
1	455	286.04	0	0	0	0	0	0	0	0	741.04	41.04
2	455	341.20	0	0	0	0	0	0	0	0	796.2	46.20
3	455	431.07	0	0	25	0	0	0	0	0	911.07	61.07
4	455	383.22	0	130	25	0	0	0	0	0	993.23	43.22
5	455	404.94	0	130	25	0	0	0	0	0	1014.94	14.93
6	455	364.88	130	130	25	0	0	0	0	0	1104.88	4.89
7	455	426.04	130	130	25	0	0	0	0	0	1166.04	16.04
8	455	455	130	130	30.78	0	0	0	0	0	1200.78	0.78
9	455	455	130	130	85.76	20	25	0	0	0	1300.76	0.76
10	455	455	130	130	162	33.92	25	10	0	0	1400.92	0.92
11	455	455	130	130	162	80	25	12.40	10	0	1459.4	9.40
12	455	455	130	130	162	80	25	55	22.93	10	1524.94	24.93
13	455	455	130	130	162	63.15	025	10	10	0	1440.15	40.15
14	455	455	130	130	126.71	20	25	0	0	0	1341.71	41.71
15	455	455	130	130	29.79	20	0	0	0	0	1219.79	19.79
16	455	343.28	130	130	25	0	0	0	0	0	1083.28	33.28
17	455	261.10	130	130	25	0	0	0	0	0	1001.1	1.11
18	455	364.58	130	130	25	0	0	0	0	0	1104.58	4.58
19	455	450.99	130	130	25	0	25	0	0	0	1215.99	15.99
20	455	455	130	130	162	44.83	25	10	0	0	1411.83	11.83
21	455	455	130	130	93.62	20	25	0	0	0	1308.62	8.63
22	455	455	130	0	58.95	20	0	0	0	0	1118.95	18.95
23	455	423.59	0	0	25	0	0	0	0	0	903.59	3.59
24	455	357.51	0	0	25	0	0	0	0	0	837.51	37.51

Table 7: Best solution of C3 with PEVs charging factor  $w = 1/2$ 

Hour	W=1/2										Demand(MW)	DSM Load(MW)
	U1(MW))	U2(MW)	U3(MW)	U4(MW)	U5(MW)	U6(MW)	U7(MW)	U8(MW)	U9(MW)	U10(MW)		
1	455	294.07	0	0	0	0	0	0	0	0	749.07	28.55
2	455	342.66	0	0	0	0	0	0	0	0	797.66	24.56
3	455	427.53	0	0	25	0	0	0	0	0	907.53	26.99
4	455	455	0	0	65.05	0	0	0	0	0	975.05	3.44
5	455	419.85	130	0	25	0	0	0	0	0	1029.85	22.38
6	455	381.31	130	130	25	0	0	0	0	0	1121.31	18.86
7	455	431.85	130	130	25	0	0	0	0	0	1171.85	13.83
8	455	455	130	130	38.01	0	0	0	0	0	1208.01	7.61
9	455	455	130	130	85.38	20	25	0	0	0	1300.38	0
10	455	455	130	130	162	33.46	25	10	0	0	1400.46	0
11	455	455	130	130	162	77.70	25	10	10	0	1454.7	0
12	455	455	130	130	162	80	25	55	10.46	10	1512.46	0
13	455	455	130	130	162	43.07	25	10	10	0	1420.07	0
14	455	455	130	130	105.85	20	25	0	0	0	1320.85	0
15	455	455	130	130	41.68	0	0	0	0	0	1211.68	1.78
16	455	355.58	130	130	25	0	0	0	0	0	1095.58	28.93
17	455	277.44	130	130	25	0	0	0	0	0	1017.44	16.89
18	455	382.85	130	130	25	0	0	0	0	0	1122.85	20.56
19	455	455	130	130	37.99	0	0	0	0	0	1207.99	0
20	455	455	130	130	162	38.91	25	10	0	0	1405.91	0
21	455	455	130	130	89.31	20	25	0	0	0	1304.32	0
22	455	455	0	0	162	24.80	25	0	0	0	1121.8	12.32
23	455	434.72	0	0	25	0	0	0	0	0	914.72	12.92
24	455	374.77	0	0	0	0	0	0	0	0	829.77	11.02

PEVs load considered in this paper is only a small part of the overall load demand in the power system, the optimal scheduling strategy could significantly reduce economic cost. With the scale of PEVs increases, the intelligent DSM method is potential to bring huge benefits to the whole system. It should also be noted that for the current PEVs charging infrastructure and users expectation, it is not realistic to make all the PEVs chargers to be coordinately controlled. The proposed charging factor  $w$  would provide a proper index in power system scheduling to balance the uncoordinated and coordinated PEVs load.

As a result, it can be concluded from the above experimental results that the proposed BCSO/CSO algorithm has shown competitive performance in solving the highly dimensional and complex PDUC problem. The level of uncoordinated PEVs charging has important impact on the power system economic cost. Moreover, the DSM of PEVs together with the UC optimization procedure, could effectively schedule the PEVs charging distribution and bring

considerable economic benefit and energy savings. Such intelligent scheduling strategy would also shift the peak load and fill the valley, providing a holistic solution to the balance of PEVs charging load management.

## 6. Conclusion

In this paper, a parallel optimization framework was proposed for solving the novel mixed-integer and multimodal PDUC problem, which simultaneously coordinates the unit commitment problem and the demand side management for plug-in electric vehicle charging load. The proposed framework is solved by real-valued/binary CSO algorithm, where the real-valued CSO was adopted to optimize the demand side load of PEVs and a binary CSO algorithm is proposed to determine the unit status according to the system characteristic. Then, a weighting factor  $w$  was adopted to evaluate the influence on power system with different ration between uncoordinated charging load and demand side load.

Table 8: Comparison of different  $w$  for the 10 unit benchmark system

W	Cost(\$/day)			Time(s)	Std(\$)
	Best(\$)	Mean(\$)	Worst(\$)		
1/4	573144.46	573246.95	573640.81	15.47	88.62
1/3	573912.07	574027.88	574269.33	15.41	125.09
1/2	574047.21	574260.66	574442.98	15.51	168.46
2/3	575028.95	575073.59	575301.92	15.31	80.88
3/4	575111.39	575264.02	575656.42	15.54	217.70
4/5	575869.97	575883.31	575909.91	15.57	13.51

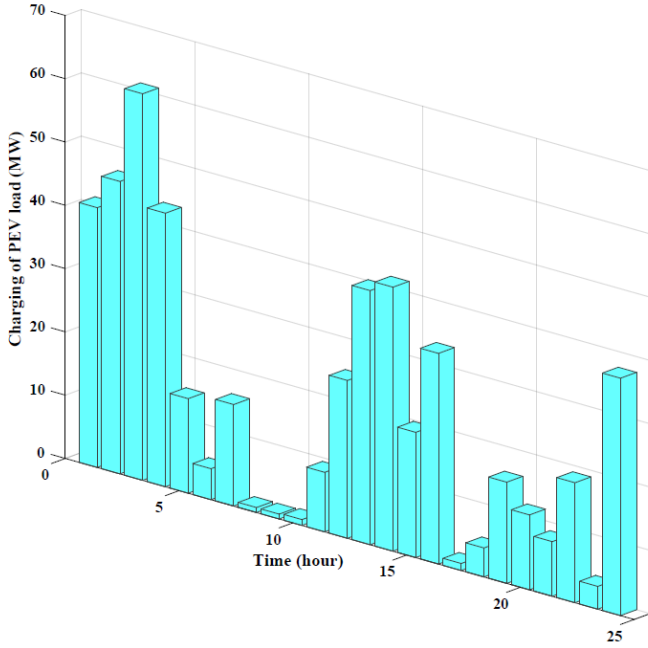


Figure 6: The curve of PEVs actual charging load

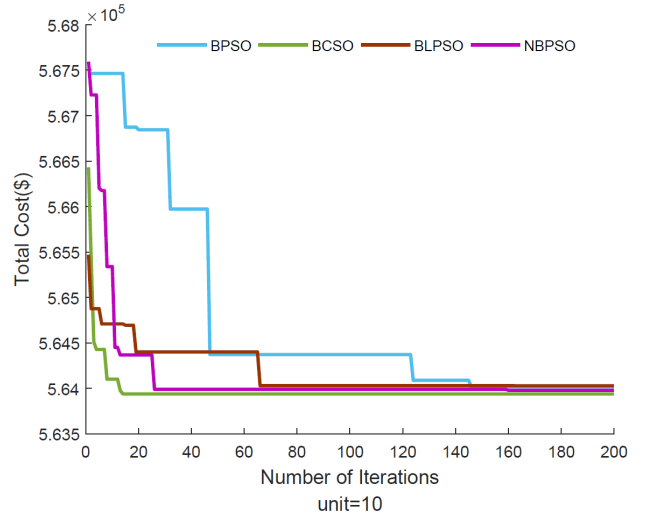


Figure 7: Optimal convergences using different algorithms for 10 unit benchmark problem

778 Numerical studies of three featured cases have been 798  
779 conducted and the experimental results have been com- 799  
780 prehensively analyzed. The 10 units benchmark case study 800  
781 has proved the applicability and stability of BCSO algo- 801  
782 rithm in solving unit commitment problem. In addition, 802  
783 the parallel BCSO/CSO problem could effectively solve 803  
784 the PDUC problem and obtain optimal results for both 804  
785 UC and PEVs charging load. Through further analysis, 805  
786 0.4% economic cost could be effectively reduced by in- 806  
787 creasing the proportion of flexible DSM of PEVs under 807  
788 the medium size of PEVs integration. Moreover, the novel 808  
789 scheduling strategy of PEVs charging load could effectively 809  
790 realize the peak shaving and valley filling for the power 810  
791 system. The superior performances of parallel framework 811  
792 with CSO/BCSO algorithm valid that the proposed algo- 812  
793 rithm is a powerful tool in solving such large scale complex 813  
794 power system scheduling problem with large penetration 814  
795 of plug-in electric vehicles. 815

796 It could be expected that with the dramatically incre- 816  
797 ase of PEVs and the schedulable power demand, plug- 817

in electric vehicles are potential to bring unprecedented benefit to improve the energy efficiency and reduce the fossil fuel cost. Therefore, the future work will consider the problems combining with wind and solar and other intermittent renewable resources, and the comprehensive evaluation of the economic, environmental impacts from the operation perspective, as well as the revenue from users perspective.

## Acknowledgements

This research is financially supported by China NSFC (51607177, 61773252 and 61876169); Natural Science Foundation of Guangdong Province (2018A030310671); China Post-doctoral Science Foundation (2018M631005); European Commission’s Horizon 2020 project, “Demand Response Integration tEchnologies: unlocking the demand response potential in the distribution grid” (DRIVE, 774431); Outstanding Young Researcher Innovation Fund of Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences (201822), and Shenzhen Discipline Construction Project for Urban Computing and Data Intelligence.



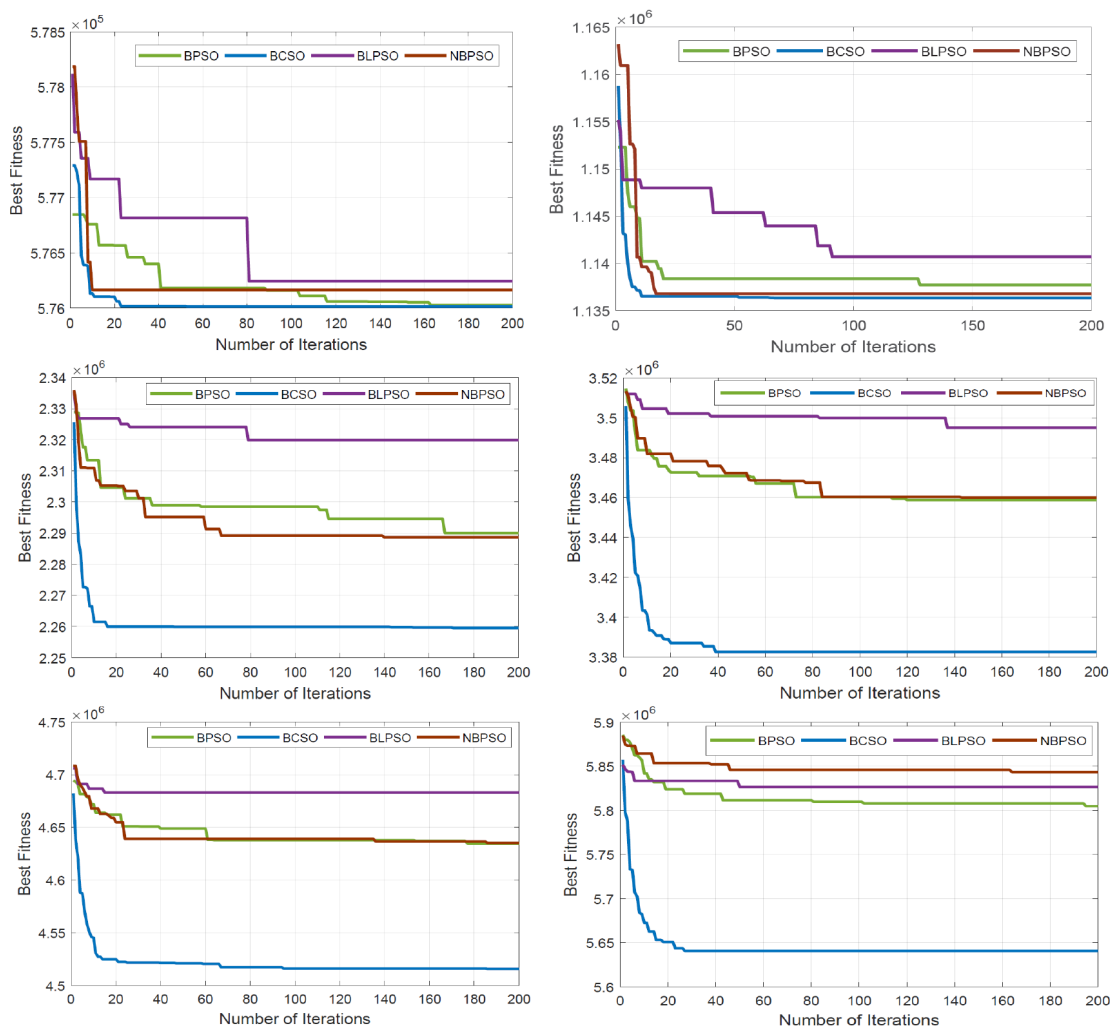


Figure 8: Simulation results of different algorithms for solving unit numbers

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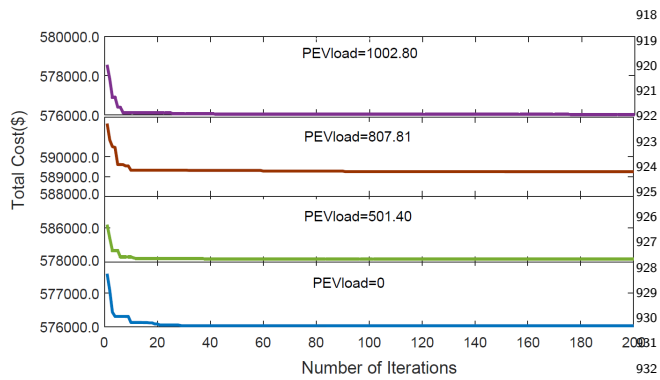


Figure 9: Comparison of different load scales of C2-s1 under 10 unit power system

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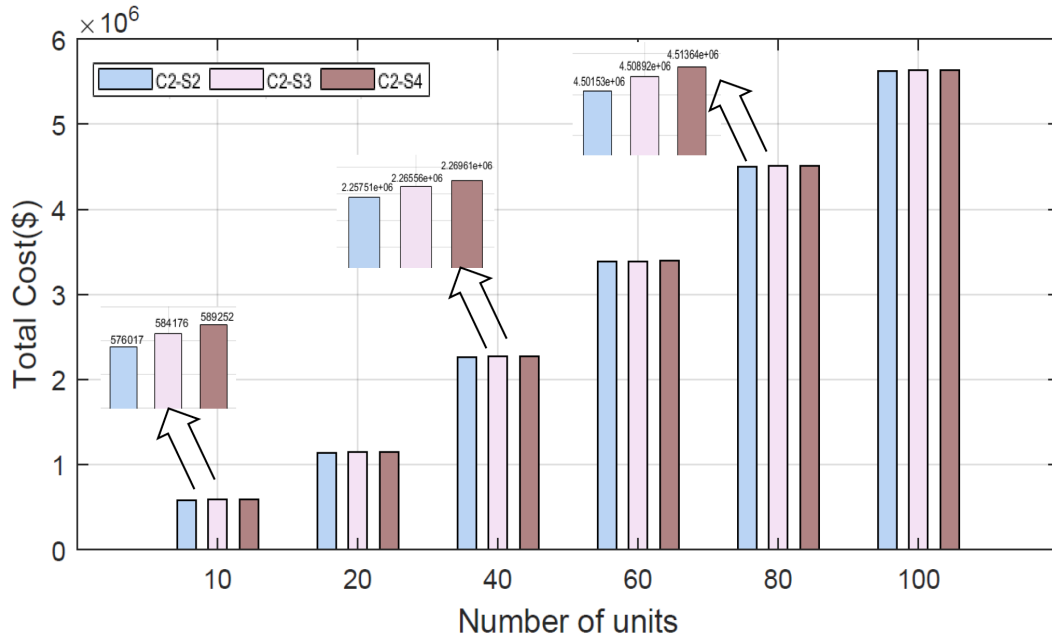


Figure 10: Optimal values comparison for all sub-cases in C2

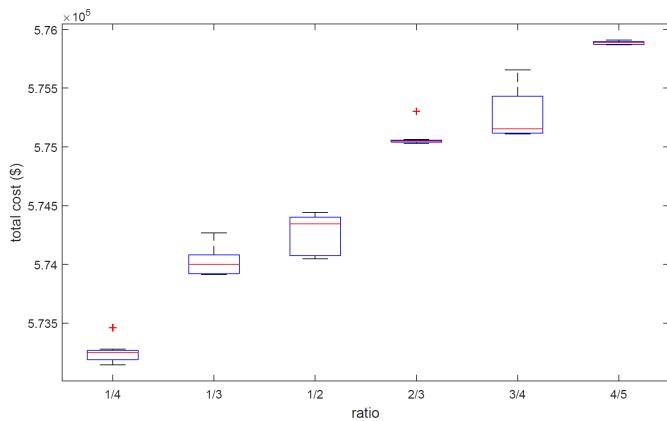


Figure 11: Optimal solution distribution for different  $w$  scenarios

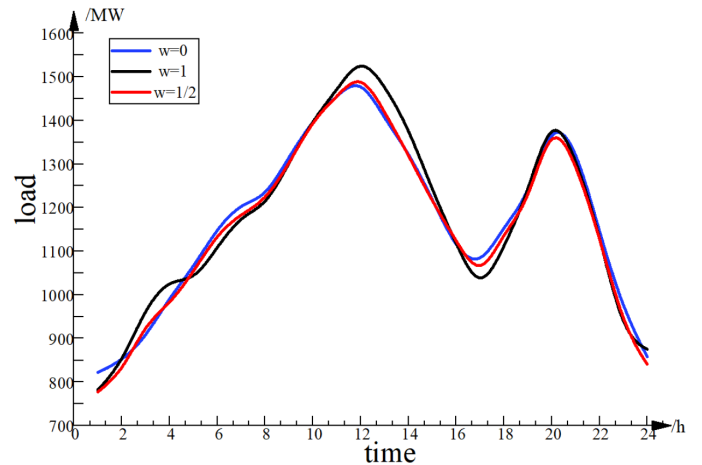


Figure 12: Optimal accumulated power demand curve under different  $w$  scenarios

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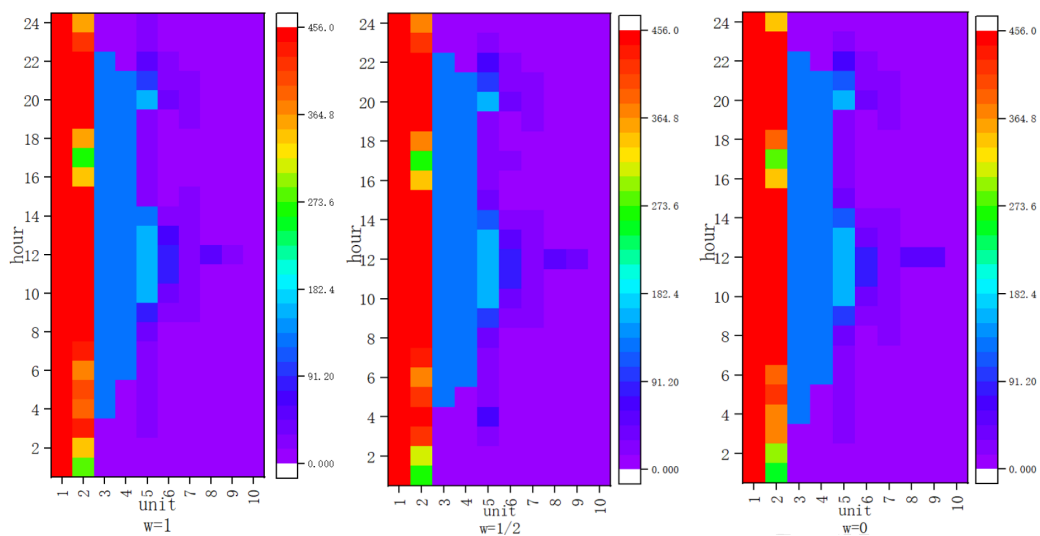


Figure 13: Optimal power output of 10 unit system when  $w = 1/2$

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