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.

Nomenclature

- a_j, b_j, c_j Coefficients of fuel cost for unit j
- $F_{j,t}$ Fuel cost of unit j at time t
- m Ratio coefficient
- MDT_j Minimum down time of unit j
- MUT_j Minimum up time of unit j
- n Number of units
- Np Number of particles
- $P_{D,t}$ Power demand at time t
- $P_{j,max}$ Maximum power limits of unit j
- $P_{j,min}$ Minimum power limits of unit j
- $P_{j,t}$ Determined power of unit j at time t
- $P_{PEV,t,max}$ Maximum charging power of PEVs at time t
- $P_{PEV,t,min}$ Minimum charging power of PEVs at time t
- $P_{PEV,total}$ Total necessary charging power
- $P_{PEV,t}$ Demand side management of PEVs at time t
- $P_{PEVload,t}$ Uncoordinated charging load of PEVs at time t
- $S(V_{l,k})$ V-shape transfer function
- SR_t Spinning reserves at time t
- $SU_{C,j}$ Cold-start cost of unit j at time t
- $SU_{H,j}$ Hot-start cost of unit j at time t
- $SU_{j,t}$ Start-up cost of unit j at time t
- T Total scheduling hours
- $T_{cold,j}$ Cold-start hour of unit j
- $TOFF_{j,t}$ Off-line duration time of unit j
- $TON_{j,t}$ On-line duration time of unit j
- TPC_{Tn} Total economic cost
- $u_{j,t}$ Binary status of unit j at time t
- $V_{l,k}$, $V_{w,k}$ Velocity of the losers and winners in the k^{th} competition

w	Weighting factor of PEVs charging load
$X'_{b,k}(t)$	Mean position value of the whole binary swarm particles
$X'_k(t)$	Mean position value of the whole swarm particles
$X_{b,l,k}$, $X_{b,w,k}$	Position of the binary losers and winners in the k^{th} competition
$X_{l,k}$,$X_{w,k}$	Position of the losers and winners in the k^{th} competition
ACO	Ant colony optimization
BCSO	Binary competitive swarm optimization
BDE	Binary differential evolution
BGSO	Binary glowworm swarm optimization
BLPSO	Best parallel particle swarm optimization
BPSO	Binary particle swarm optimization
brGA	Binary-real-code genetic algorithm
CSO	Competitive swarm optimizer
DBDE	Discrete binary differential evolution
DCSO	Dynamic competitive particle swarm optimizer
DE	Differential evolution
GAs	Genetic algorithms
HPSO	Hybrid particle swarm optimizer
IBSO	Improved binary particle swarm optimization
ICSO	Improved competitive swarm optimization
IPSO	Improved particle swarm optimization
MA	Meta-heuristic algorithms
MCSO	Modified competitive swarm optimizer
NBPSO	New binary particle swarm optimization
OLCSO	Orthogonal learning competitive swarm optimizer
PSO	Particle swarm optimization
QPSO	Quantum-inspired particle swarm optimization
SA	Simulated annealing

1. Introduction

Transport accounted for around 29% of global final energy demand and 7.7Gt of energy related CO_2 emissions [1]. Sectoral CO_2–equivalent emissions of 7.0 $GtCO_2e$ and 7.7 $GtCO_2e$ 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].

1.1. Motivation

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].

1.2. State of the art

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 nonlinear, large-scale, mixed integer and high dimension features, where many attempts have been made for solving the intractable problem. Existing conventional mathematical based approaches, such as the dynamic programming [13], integer programming [14], mixed-integer programming [15, 16], branch and bound methods [17] and Lagrangian relaxation methods [18, 19], are able to achieve sufficient results given limited range problems, whereas they are prone to encounter dimension disasters under high complexity and large scale scenarios. With the fast development of the meta-heuristic algorithms (MA), their advantages in problem modeling flexibility and searching efficiency have proved to be sufficient for solving UC problem [20, 21]. Popular MAs have been utilized including genetic algorithms (GAs) [20, 22], simulated annealing algorithm (SA) [23, 18], particle swarm optimization (PSO) [24], ant colony optimization (ACO) [25] and teaching learning based optimization (TLBO) [26] and etc. In addition, specific variants of popular MAs have also been applied to the UC problem, such as binary particle swarm optimization (BPSO) [27], quantum-inspired particle swarm optimization (QPSO) [28] and hybrid particle swarm optimization (HPSO) [29] etc. Though numerous methods have been proposed, the optimal solutions for high dimensional UC problems have not been obtained yet, adding that the emergence of large penetration of PEVs would address new difficulties to the system.

Driven by policy stimulus and rapid progress in science and technology, PEVs have been rapidly popularized. On one hand, PEVs would be potential to bring considerable benefits to the environment and economy. On the other hand, their large quantity power demand and stochastic charging behaviors would impose significant impact on the power systems [30, 31]. In addition, due to gradual expansion of the unit scale as well as the high degree of non-linearity and coupling characteristics, the optimal economic operation and coordination for the power system and PEVs have become extremely challenging [32, 33]. Therefore, intelligent scheduling for power units and PEVs is an inevitable and arduous task, where numerous computational methods have been proposed [34, 35, 36, 37]. Saber et al. [38, 39] proposed PSO based cost and emission reduction in a smart grid by utilization of grid vehicles and renewable energy sources. Talebizadeh et al. [40] explored the economic impacts of PEV charging and discharging in the UC problem using GA and differential evolution (DE) methods. Yang et al. [41, 21] proposed BPSO based hybrid meta-heuristic methods for solving hybrid UC problem considering intelligent scheduling of PEVs. Jian et al. [42] proposed the valley filling algorithm for PEVs aggregators. ARIMA-based methods and game theory were employed to forecast the PEVs loads and optimize charging cost [43, 44, 45]. Multi-objective approaches [46, 47, 48, 49] have also been proposed to simultaneously minimize the emission and economic costs of power unit and PEVs in power system. The majority of existing methods consider the PEVs as an aggregator and scheduling the charging and discharging under fully coordinated or uncoordinated scenarios. However, very few studied have considered the impact of different scales of PEVs charging load coordinated with demand side management 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 exploitation 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 between 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 performance of convergence speed and result accuracy is significant, particularly in solving large scale problems [51]. Recent 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 variants of CSO algorithm, for example, modified competitive swarm optimizer (MCSO) [52], orthogonal learning competitive swarm optimizer (OLCSO) [53], dynamic competitive swarm optimizer (DCSO) [54] and improved competitive particle swarm optimizer (ICSO) [55] have been proposed 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 accessed 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 comment. 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 simultaneously solving coordinate unit commitment and demand side management of plug-in electric vehicles is proposed, named as the PDUC problem. A real-valued competitive swarm optimization method is used to optimize the demand side load flexible access to power system, adjust the unordered charging load and decrease the load of power system during the peak period. The unit status is only scheduled using a binary algorithm because of its unique binary switching and large-scale characteristic. Therefore, a binary competitive swarm optimizer has been improved based on the CSO algorithm for optimizing 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 numerical experiments has been conducted to prove the feasibility 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.

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

The objective function consists of two components: the fuel economic cost and the start-up cost of units, where TPC_{Tn} 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,

$$F_{j,t}(P_{j,t}) = a_j + b_jP_{j,t} + c_jP_{j,t}^2 \tag{2}$$

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),

$$SU_{j,t} = \begin{cases} SU_{H,j},\ if\ MDT_j \le TOFF_{j,t} \le MDT_j + T_{cold,j} \\ SU_{C,j},\ if\ TOFF_{j,t} > MDT_j + T_{cold,j} \end{cases} \tag{3}$$

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 to the system stable operation. In order to achieve the optimal objective function and ensure the secure and economic operation of the system, various equality and inequality constraints of the units and PEVs, for example the power demand limit and charging bound limit, should be considered.

2.2.1. Power balance constraint

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

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

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

2.2.2. Generation limit constraint

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

$$u_{j,t}P_{j,min} \leq P_{j,t} \leq u_{j,t}P_{j,max} \tag{5}$$

where $P_{j,min}$ and $P_{j,max}$ represent minimum and maximum power capacity respectively, while the generation output of j^{th} unit should be within the unit contribution boundaries.

2.2.3. Minimum up/down time limit constraint

The status of units only have binary options: '1' 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),

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

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

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

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.

$$SR_t = m \times P_{D,t}. \tag{8}$$

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),

$$P_{PEV,t,min} \leq P_{PEV,t} \leq P_{PEV,t,max}. \tag{9}$$

where the $P_{PEV,t,min}$ denotes the minimum charging power of PEVs at time t, and $P_{PEV,t,max}$ is the maximum boundary restriction. The both boundaries largely depend on the number of PEV aggregation and the capacity of each participants. 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):

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

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):

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

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 $P_t = (x_{(1)}, x_{(2)}, ...x_{(n)})$. Suppose the dimension of particle is n, the positions of these particles are denoted by $X_i(t) = (x_{(i,1)}(t), x_{(i,2)}(t), ...x_{(i,n)}(t))$, and the velocity of these corresponding particles is denoted by $V_i(t) = (v_{(i,1)}(t), v_{(i,2)}(t), ...v_{(i,n)}(t))$. 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:

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

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

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 $k = 1, 2, ..., m/2$. $R_1(k,t)$, $R_2(k,t)$ 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 ϕ 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).

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

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

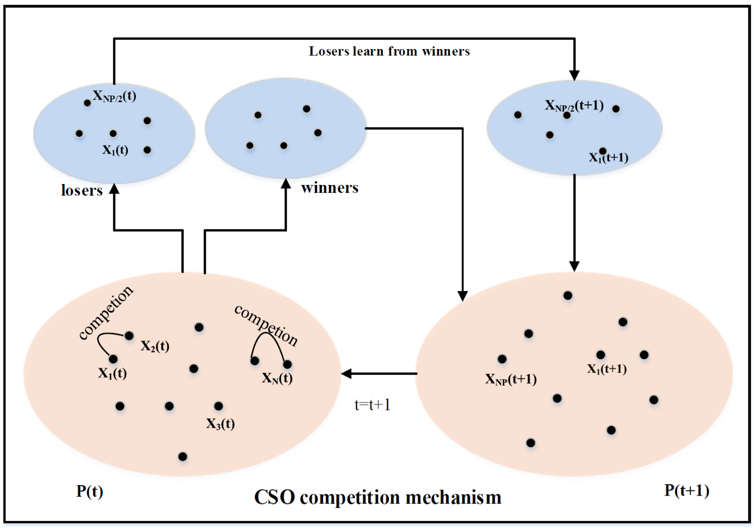

Figure 1: The competitive mechanism of CSO algorithm

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).

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

$X_{b,l,k}(t+1)$ 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 vise 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

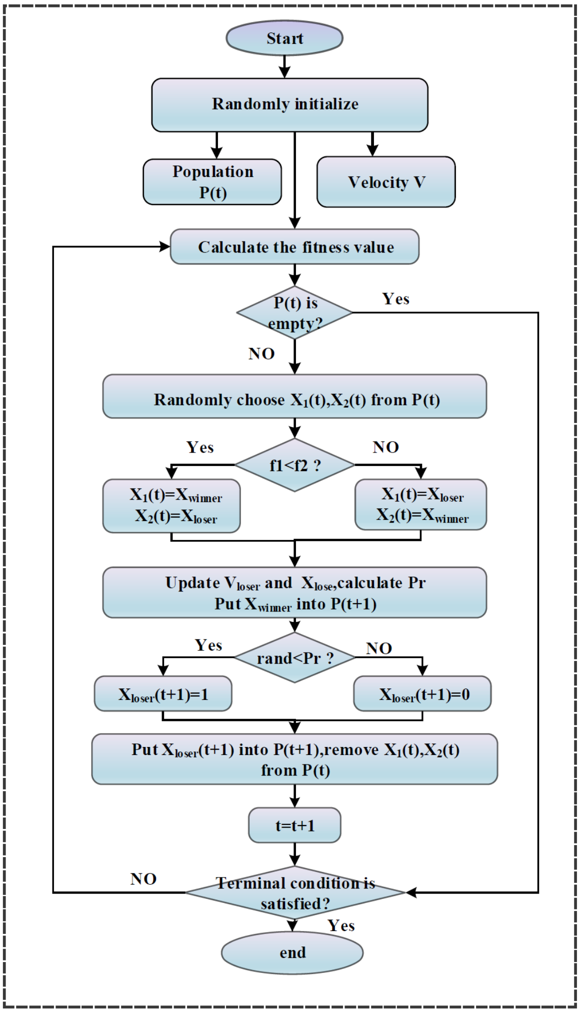

Figure 2: The principle diagram of BCSO algorithm

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 :

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 ϕ 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 ϕ 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 ϕ 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

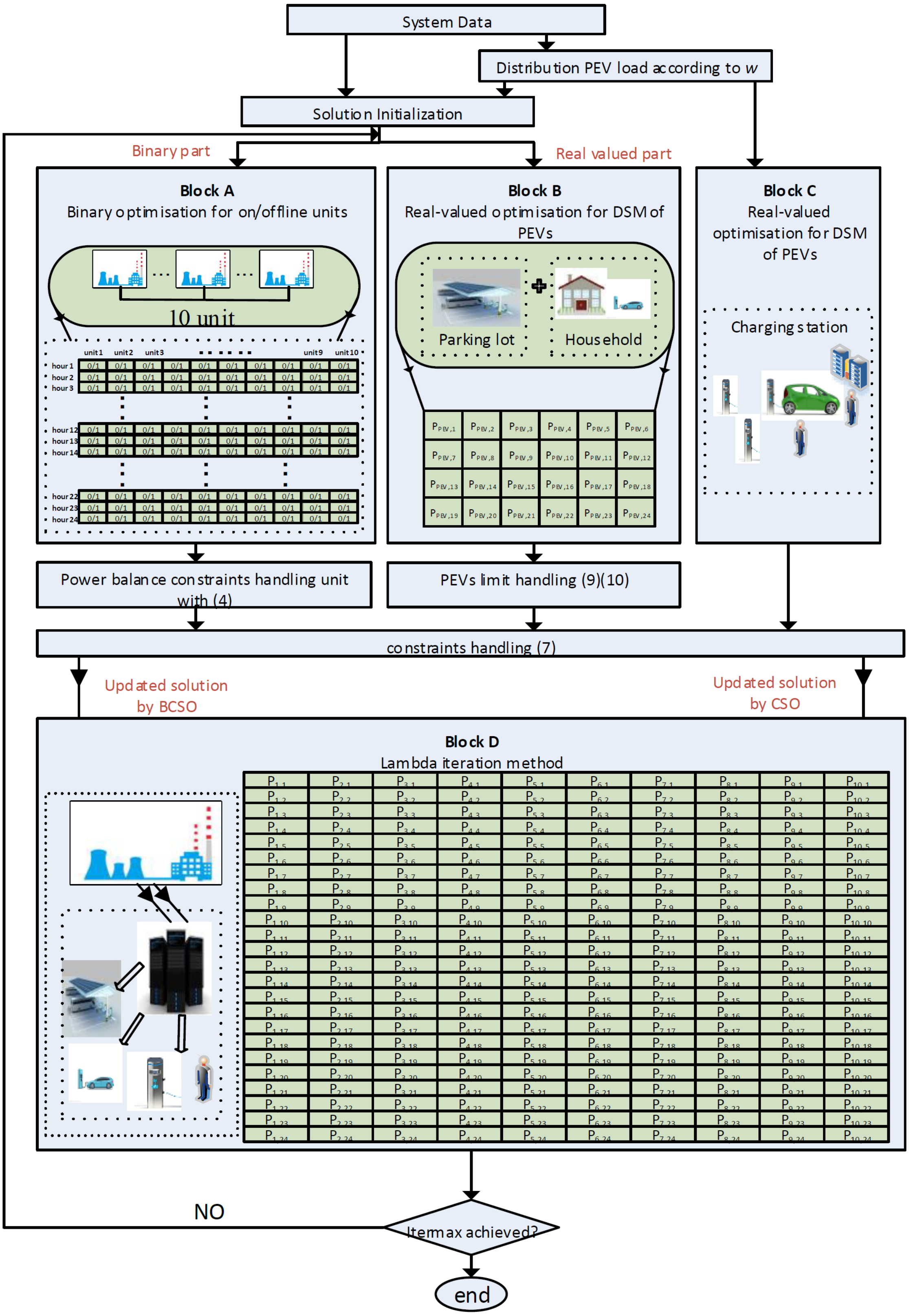

Figure 3: The schematic of proposed method for solving the PDUC problem

scales ranging from 10-100 with the integration of several levels of uncoordinated charging of PEVs, demonstrating 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-

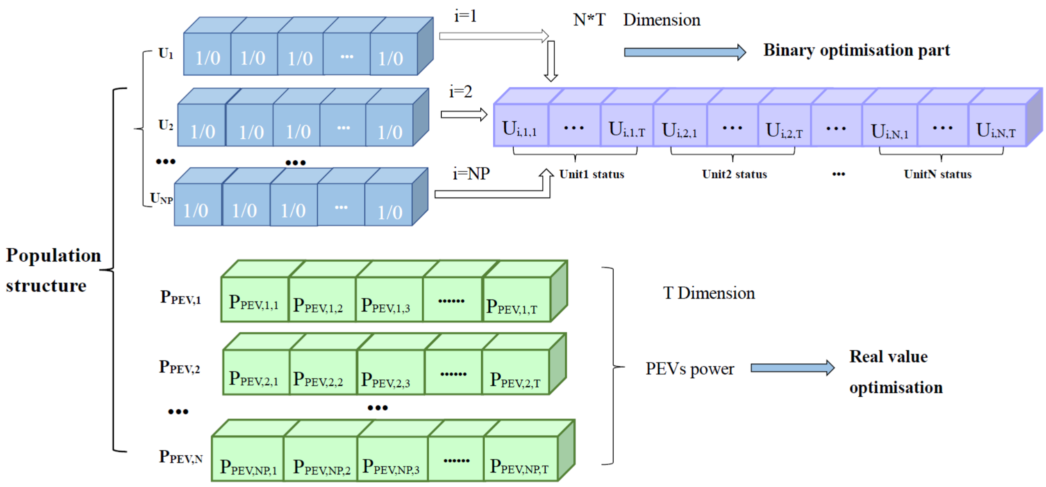

Figure 4: Structure of a population for the proposed parallel optimization algorithm

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^2)	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 counterpart 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 values 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 stability 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 significant 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 issue 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 subcase C2-S1 aims to compare the different unit scales with fixed PEVs charging load, whereas sub-cases C2-S2 and

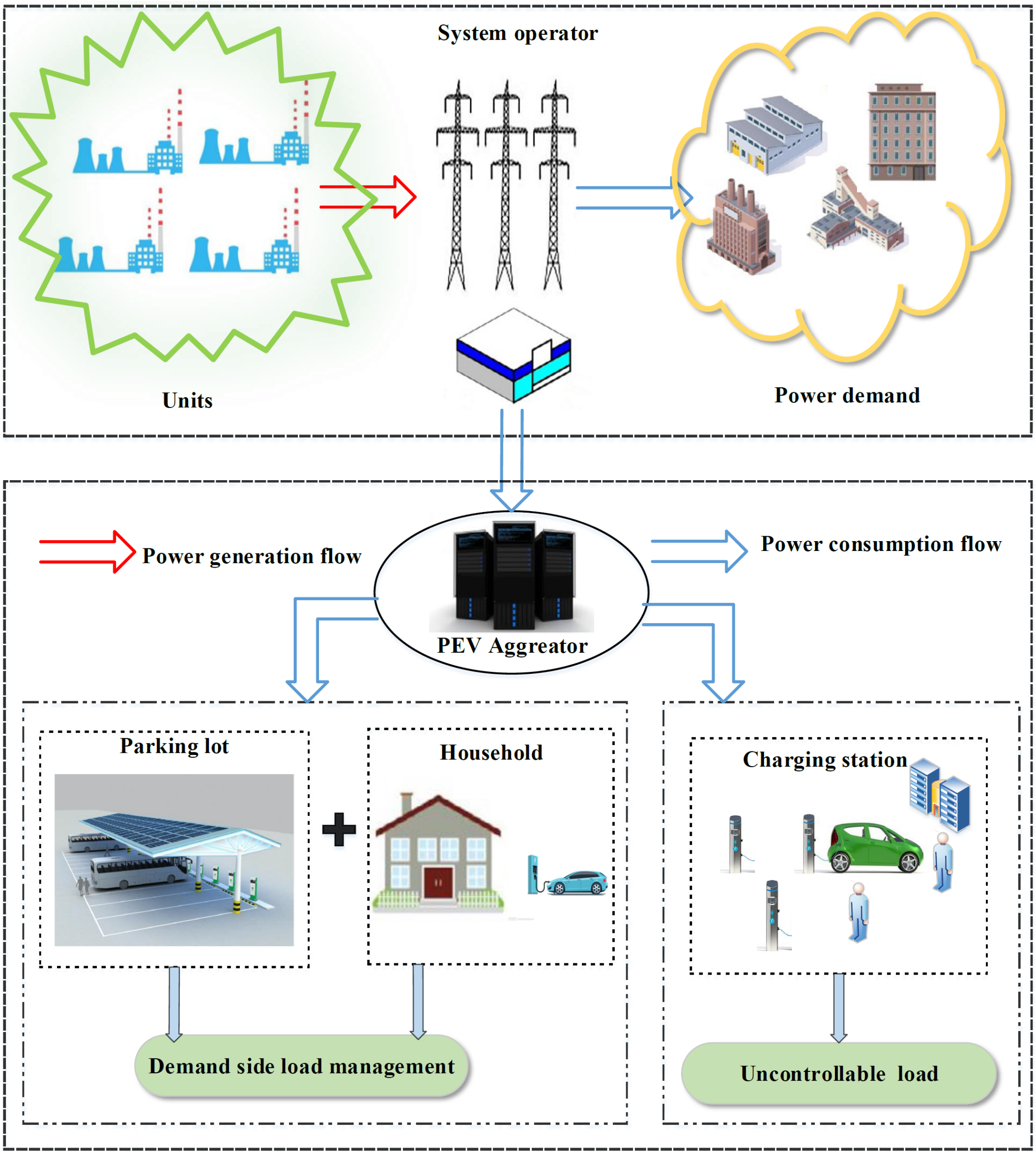

Figure 5: Three categories of PEVs load

C2-S3 compare the 10 unit benchmark with various PEVs uncontrollable load. The actual charging load of PEVs in a Shenzhen city during 24-hour one day time horizon has been integrated, which is shown in Figure 6. The PDUC problem is optimized by the proposed BCSO algorithm with the same algorithm parameter settings with Case 1, and 10 independent runs are conducted for all the sub-cases in Case 2 to eliminate the randomness.

5.2.1. C2-S1: Different unit scales with fixed uncoordinated charging load level

In sub-case C2-S1, different unit scales have been adopted, and a fixed PEVs uncoordinated charging load with a total of 501.40MW shown in figure 6 is integrated within the multiple unit scales, including 10, 20, 40, 60, 80 and 100 units. The three BPSO variants including BPSO, NBPSO, BLPSO [41] have been adopted in the algorithm comparison. 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 increased 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. Figure 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	***563937.68***	***563937.68***	***563937.68***	0.00	11.58

Table 3: Parameter tuning for BCSO and BPSO

C2-S1: PEV load=501.40MW									
		unit=10				unit=100			
Method	factor	Best($)	Mean($)	Worst($)	Time(s)	Best($)	Mean($)	Worst($)	Time(s)
	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
BCSO	0.10	***576017.28***	***576022.63***	***576027.98***	***16.69***	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
ϕ	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	***5622547.17***	***5623415.79***	***5623725.21***	***89.41***
	0.30	576017.28	576025.34	576028.93	16.70	5622592.12	5623283.94	5623853.92	87.36
	0.55	576131.40	576389.20	576632.69	14.43	5702133.89	5713199.33	5727424.49	63.73
BPSO	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	***5697735.57***	***5712383.37***	***5729826.95***	***67.30***
	0.75	***576058.57***	***576163.24***	***576456.61***	***14.51***	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 also 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	*C2-S1*	576017.28	576022.63	576027.98	16.69	5.63
	C2-S2	584176.14	584177.39	584177.52	13.59	0.43
	C2-S3	589252.28	589258.37	589283.42	13.96	12.83
20	*C2-S1*	1136186.10	1136293.59	1136349.73	20.57	46.76
	C2-S2	1143398.55	1143556.71	1143621.00	21.43	84.92
	C2-S3	1148340.50	1148552.35	1148637.91	21.44	105.65
40	*C2-S1*	2257509.66	2257662.57	2257770.56	35.74	75.22
	C2-S2	2265563.68	2265688.78	2265819.69	38.41	95.57
	C2-S3	2269609.74	2269678.78	2269808.96	38.12	66.19
60	*C2-S1*	3379890.16	3380096.98	3380211.49	49.25	101.66
	C2-S2	3386117.59	3386515.18	3386772.51	53.15	232.00
	C2-S3	3392267.85	3392557.10	3392794.96	51.91	184.81
80	*C2-S1*	4501534.67	4501802.95	4501919.85	72.39	115.71
	C2-S2	4508923.08	4509160.25	4509531.95	75.27	200.92
	C2-S3	4513643.06	4513890.08	4514169.02	73.32	169.97
100	*C2-S1*	5622547.17	5623415.79	5623725.21	89.41	387.93
	C2-S2	5630717.16	5631031.03	5631295.54	88.16	200.67
	C2-S3	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 been 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 relief 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) Best(\$)	Mean(\$)	Worst(\$)	Time(s)	Std(\$)
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

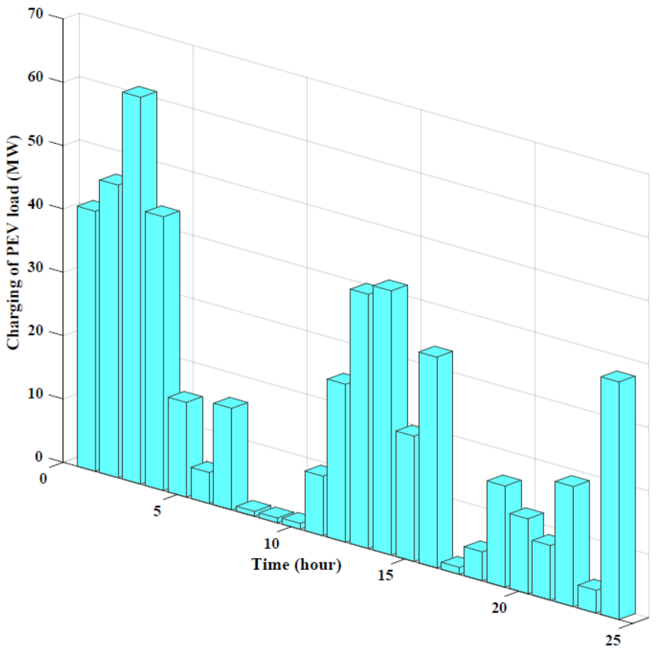

Figure 6: The curve of PEVs actual charging load

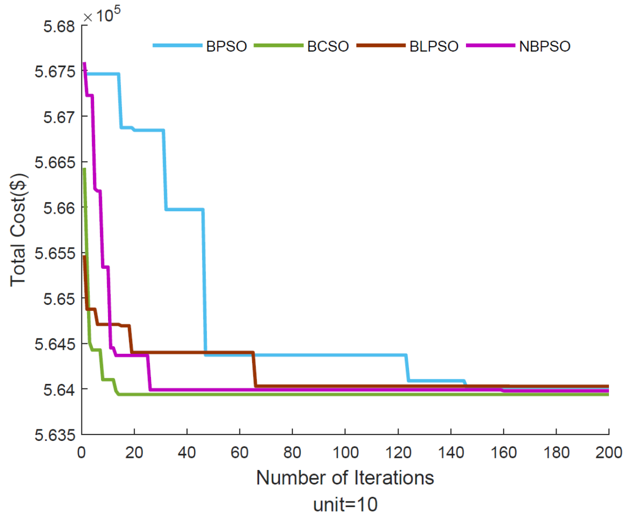

Figure 7: Optimal convergences using different algorithms for 10 unit benchmark problem

Numerical studies of three featured cases have been conducted and the experimental results have been comprehensively analyzed. The 10 units benchmark case study has proved the applicability and stability of BCSO algorithm in solving unit commitment problem. In addition, the parallel BCSO/CSO problem could effectively solve the PDUC problem and obtain optimal results for both UC and PEVs charging load. Through further analysis, 0.4% economic cost could be effectively reduced by increasing the proportion of flexible DSM of PEVs under the medium size of PEVs integration. Moreover, the novel scheduling strategy of PEVs charging load could effectively realize the peak shaving and valley filling for the power system. The superior performances of parallel framework with CSO/BCSO algorithm valid that the proposed algorithm is a powerful tool in solving such large scale complex power system scheduling problem with large penetration of plug-in electric vehicles.

It could be expected that with the dramatically increase of PEVs and the schedulable power demand, plug-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.

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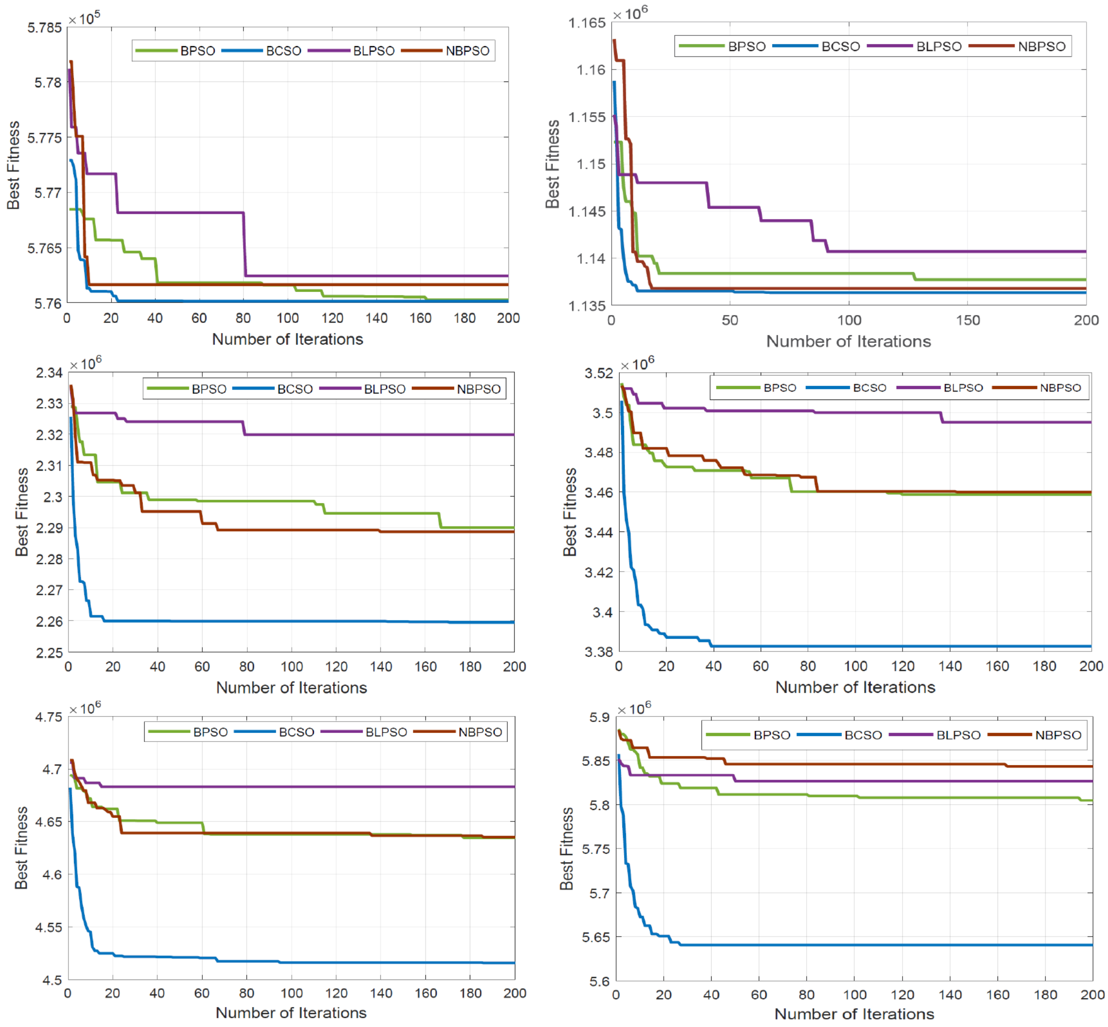

Figure 8: Simulation results of different algorithms for solving unit numbers

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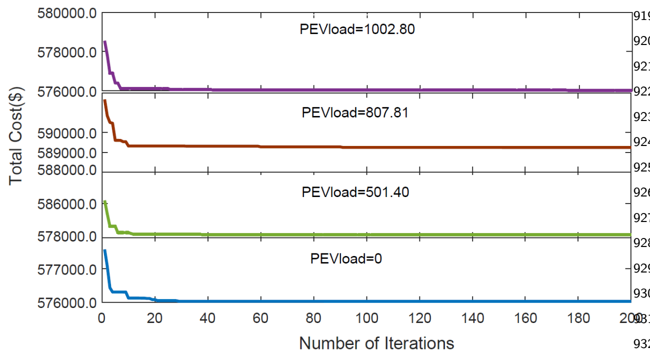

Figure 9: Comparison of different load scales of C2-s1 under 10 unit power system

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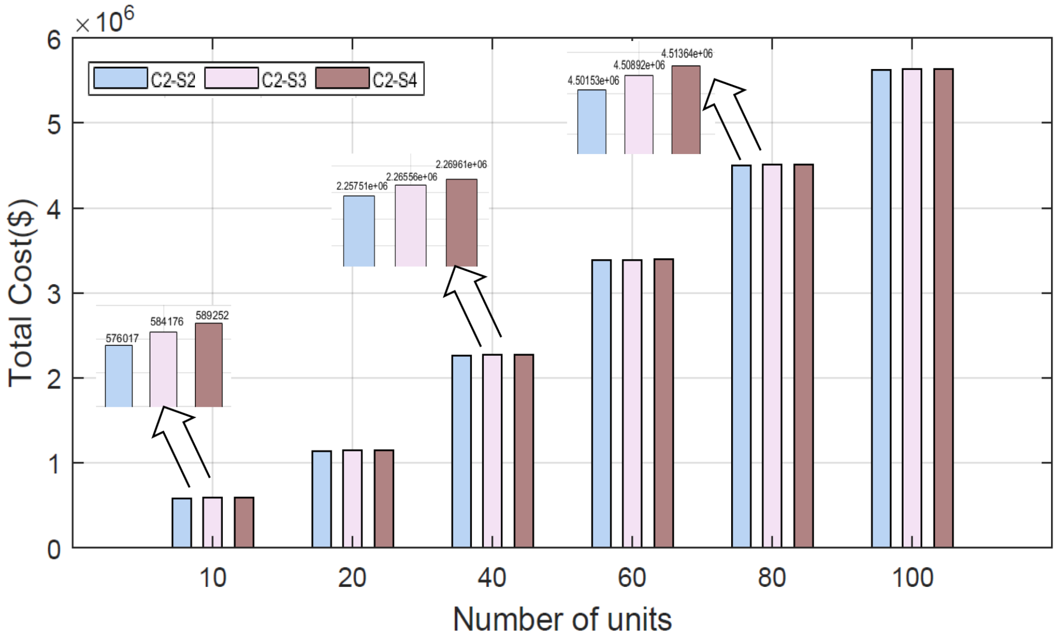

Figure 10: Optimal values comparison for all sub-cases in C2

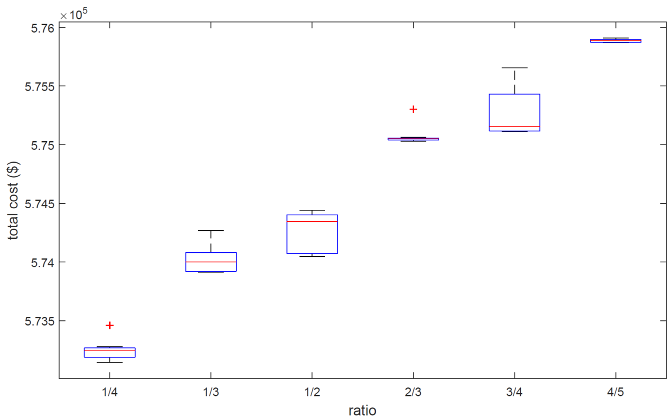

Figure 11: Optimal solution distribution for different w scenarios

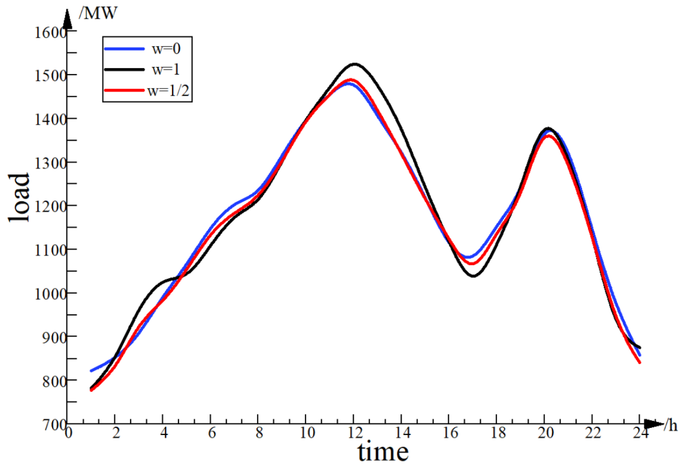

Figure 12: Optimal accumulated power demand curve under different w scenarios

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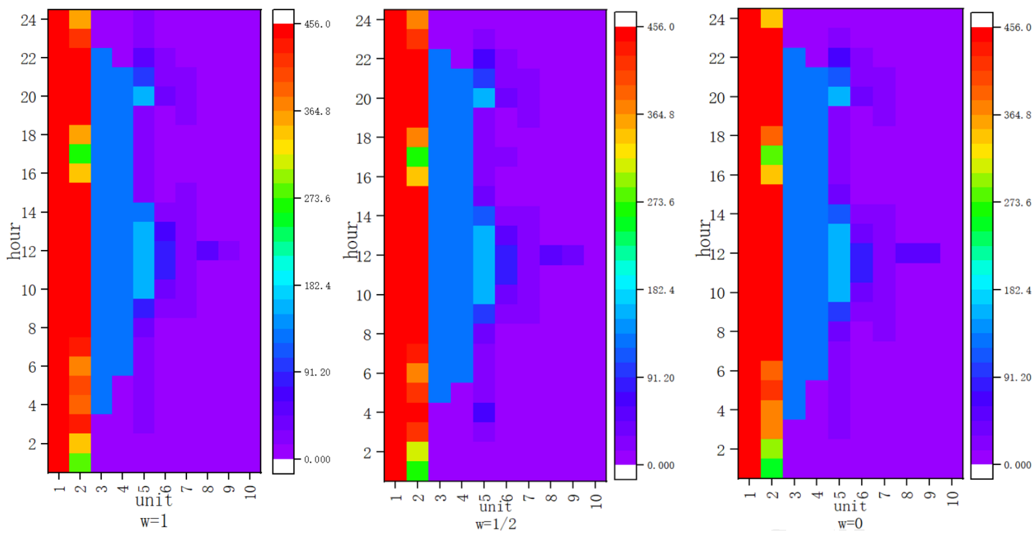

Figure 13: Optimal power output of 10 unit system when $w = 1/2$

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