PSO-based Method to Find Electric Vehicle's Optimal Charging Schedule under Dynamic Electricity Price

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***Abstract*—Owning to greenhouse effect and exhaustible gasoline, there is a need for the automobile industry to develop electric vehicles (EVs). EV owners' major concern is about how to minimize operating cost under dynamic market electricity price. Optimization of a charging scenario draws great attention from the researchers worldwide. This paper presents a particle swarm optimization (PSO) based optimization approach that can help EV owners achieve the most economical charging behavior.**

***Index Terms*—Electric vehicle; Dynamic electricity price; PSO; Optimal charging**

I. INTRODUCTION

Electric vehicles (EVs) take alternative energy sources to reduce the traditional internal combustion engine (ICE) vehicles' dependency on oil. EVs offer many obvious benefits, such as lower energy cost and greenhouse gas emissions, and the convenience to use renewable energy sources [1]. Meanwhile, as the environmental deterioration and traditional energy crisis become more and more serious in recent years, there is an increased worldwide concern at economic, environmental, industrial, and societal levels on EVs technology [2]. There is a boom in the main EV manufacturers of the United States, Europe, and Japan, such as General Motors, Coda, Tesla motors, Ford, ZAP, Volkswagen, Honda, and Toyota [3]. In 2010, Shanghai EXPO adopted electric buses to shuttle visitors at its site.

EV applications not only reduce cost and emission with respect to the use of ICE vehicles, but also provide valuable service to power systems. However, mass adoption of EVs is not without its challenges, i.e., they are typically more expensive than ICE vehicles and the public charging infrastructure is still in its infancy. Additionally, their uncontrolled charging may cause energy shortage in an energy grid [4]. Battery of an EV can be considered as a controllable load. One solution to addressing the above challenges is vehicle-to-grid (V2G), through which vehicle owners can minimize their operating cost by charging their battery at the lowest possible electricity price and releasing energy back to the grid [2, 5]. Charging during the off-peak hours will help avoiding overload of the grid. EV battery can provide V2G and G2V (grid to vehicle) capabilities, known as regulation service. This functionality is a bidirectional charging that offers ancillary service to the grid. Many researches have been done on EV optimal charging throughout the world [4]. In 2011, Sortomme and El-Sharkawi proposed optimal charging strategies for unidirectional V2G [6]. In their work, they put forward an optimization algorithm providing significant benefits to all participants: customers, aggregators, and utilities. In 2012, they proposed a V2G algorithm to maximize profits both to the aggregator and to lower the cost of EV charging to the customer [7]. In 2010, Han, et al. [8] apply a dynamic programming algorithm based on the cost function to compute the optimal charging control for each vehicle. Their work develops an aggregator for V2G frequency regulation regarding the optimal control strategy for the first time. In 2010, Acha, et al. employed a time coordinated optimal power flow formulation in which plug-in hybrid electric vehicle (PHEV) units and on-load tap-changer devices were coordinated to improve network operation [9]. In [10], optimization of the EV charging during the low cost off peak period was performed to minimize the cost of EV charging in the context of Singapore's national grid system. Guzzella and Sciarretta in [11] proposed a quadratic programming method to control and coordinate the charging of multiple vehicles in order to reduce the peak load and load profile variability observed by a distribution grid transformer. In [12], an intelligent method is given for scheduling the usage of available energy storage capacity from PHEVs and EVs. It decides whether each vehicle should buy, sell, or hold electricity at every time step that it is in a parking slot. Wang [13] used a PJM five-bus example and empirical data to analyze the potential impacts of PHEVs on locational marginal prices. The work [16] proposed a prediction-based charging scheme to obtain the lowest cost of charging under dynamic prices using the k-nearest neighbor algorithm but did not consider V2G. In [17], an Electric Vehicle-Intelligent Energy Management System was proposed based on a PSO algorism, but it only advises the customer when to charge

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or discharge at a single time. Conejo [18] proposed a novel technique to forecast day-ahead electricity prices based on the wavelet transform and ARIMA models. In this method, the application of the inverse wavelet transform to the predictions of the constitutive series allows producing accurate forecast of the original price series.

In this paper, we introduce a mathematical formulation and three different cases based on a PSO algorithm for optimizing an EV's charging schedule, given dynamic electricity prices and driving patterns. Furthermore, we provide real-time actions for EV to charge or discharge all day unlike a single time cation in [17].

The rest of the paper is organized as follows. An EV charging control architecture with appropriate assumptions is given in Section 2. Section 3 introduces intelligent optimal charging methods under the real-time market price. Section 4 shows the simulations of the PSO-based charging model. The article is concluded in Section 5.

II. EV CHARGING CONTROL ARCHITECTURE

Vehicle owners normally charge EVs under an uncontrolled scenario at a parking slot. If an EV begins charging when it is plugged in, and stops when the battery is fully charged, this can be considered to require no intelligent control on how and when to start and stop charging or give incentive to influence individual consumer behavior [12]. However the uncontrolled charging scenario may overload the peak loading and increase an individual owner's cost [14]. Therefore, an important question is when consumers to charge their vehicles. The optimum time for electricity suppliers is typically at night when the demand for electricity is low and low-cost plants are the marginal producers [14]. It will be important for utilities to provide incentives for customers to shift their demand to off-peak times, through such policies as time-of-use price, real-time price, and charge management. They need to implement the technologies necessary for automated control of charging. This includes smart chargers, meters, and other information technology to track and control vehicle loads [14]. If real-time electric pricing is implemented, vehicle owners might want to store power in their vehicles to either drive during daytime or sell during peak pricing [12], since vehicles are likely to park in a typical parking slot capable of buying and selling electricity power [12].

Due to the shortage of the electricity power and the increasing gasoline consumption, many countries propose real-time spot electricity pricing strategies to regulate the owners' charging and discharging behavior [19, 20, 21]. Hence, the price is a time-varying parameter. It is much cheaper during off-peak loading. Thus, it is predictable that charging EVs at night costs less. The real-time strategy will give incentive to EV owners to charge when electricity prices are low and discharge power back to the grid when the price is high. This strategy can alleviate the load during peak loading and increase the load during off-peaking load, called eliminating the peak and filling the valley of grid load. Our research is based on the hypothesis that vehicles can charge and discharge with the variable electricity prices in a typically parking slot where the plug-in utilities are available.

In general, two kinds of control architectures can be deployed for the optimal charging of EVs, i.e., centralized and decentralized control. Their difference lies in the deployment of the controller in different positions. For centralized control, the controller is put on the aggregator level, and for decentralized control, the controller is located at the individual EV level. Both have their advantages and disadvantages. For centralized control, the aggregator can aggregate a large number of EVs and then have more competence in the electricity market, e.g, buying cheaper electricity and providing ancillary service to the grid in a more stable fashion. However, the system operator would require significant communication ability with EVs do not pose strict powerful computation capability. Decentralized control can release the highly requirement on communication, but its drawback is that each individual EV needs to collect and store its trip history and that, if EVs need to consider their charging schedule with grid constraints, the need for communication is also high.

This work only considers a control strategy applicable to both architectures. In other words, we concentrate on the optimal control strategy level. There exists an underlying assumption, i.e., the existance of contracts between aggregator and consumers, which enable the aggregator send explicit control signal to charge or discharge their EVs [18]. In order to achieve the optimal control, the following assumptions are made:

1) The aggregator is set up to be a price taker only, it does not affect the electricity price.

2) The electricity price is assumed to be known. Price forecasting is assumed to be possible. In the reality, the aggregator may predict the electricity spot price.

3) Automated real-time communication exists to enable the smart charging, i.e., all information of EVs can be immediately communicated to the aggregator, and the control signal generated by the aggregator can be delivered to EV.

4) A future driving pattern is obtained by estimating mining past trips or is given by an EV user. Electricity demand of every trip is also known based upon it.

In this work, only one vehicle's charging schedule is studied, and the grid constraints will not be considered in the following discussions. In addition, some possible negative influence is ignored for simplicity, i.e., frequently charging the vehicle may shorten the life time of its battery and other additional costs (time wasted in charging the vehicle, etc.).

III. INTELLIGENT OPTIMAL CHARGING METHODS UNDER REAL-TIME MARKET PRICE

In this section, a case is studied and the goal of optimization is to present a charging strategy for every individual vehicle to minimize the cost of electricity while satisfying the vehicle owner's requirements. In this case, a vehicle is plugged in whenever its driving task is finished.

A. Problem description

In this paper it is assumed that typical activities take place from 8:00 AM to 8:00 AM in the next day. The charging schedule is divided into 288 5-minute time intervals. The period starts from the first second when the vehicle owners begin their first trip and ends right before the next day's departure. As mentioned previously, the objective function is to ensure that the battery is fully charged before the first trip of the following morning, which means $x_0 = 100\%$ and $x_{288} = 100\%$. The vehicle used to study in this paper is a battery pack, which is a purely electricity propulsion system. The basic battery information is listed in Table I together with others. U is defined as the set of admissible states which indicate the possible control signals which falling into [0,1]. X is defined as the set of admissible states which indicate the possible state of charge (SOC) of the battery, which ideally falls into [0%, 100%]. Δt is time interval, which is defined as 5 minutes. Moreover, it is important to know driving patterns, which includes the departure time, return time and energy requirements of every trip. Based on the vehicle parameters, a driving map includes three trips during a day is given in Table II.

Another important information is electricity price, which is based upon a typical work day of from the Nordpool Spot market area of Denmark [15]. The day-ahead real-time pricing curve is shown in Fig. 1. To obtain an optimal charging schedule, prices for electricity service are prerequisite.

TABLE I
SIMULATION PARAMETERS

Battery	Value
Total capacity	50Ah
Maximum Energy Storage	18.4KWh
Maximum plug power	4KW
Internal resistance	0.0025ohm
Discretization	Parameters
U	[0,1]
X	[0%,100%]
Δt	5min

TABLE II
DRIVING BEHAVIOR

Trip	Departure Time	Return Time	Energy Requirement
1	8:00	9:00	11.04KWh
2	15:00	16:00	13.25KWh
3	20:00	21:00	11.04KWh

In our previous work [18], two charging methods are investigated: fast charging and dynamic programming. Fast charging is a kind of uncoordinated charging. It assumes that vehicles owners face a flat price throughout the whole day and consequently their vehicles are charged instantaneously when they are plugged in, and the batteries will be fully charged as fast as possible without considering the daily electricity price. The strategy provides customers with flexibility, however, the electricity cost is likely high. The idea of the dynamic programming-based charging method is to obtain an optimal charging schedule to minimize the charging cost.

Clearly, to minimize the charging cost, EV should be charged when the electricity price is the lowest. And the battery does not have to be fully charged before the next trip. Instead, it would be sufficient if it is charged enough to support the energy consumption for the next trip. This leads to an electricity cost lower than the fast charging cost. Although a dynamic programming charging schedule is more effective than fast charging, the total computation time is large. Hence, we aim to introduce a more efficient method to optimize a charging schedule.

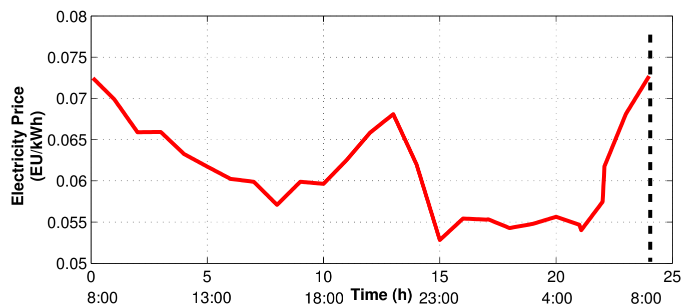

Fig. 1. Profile with Electricity Price

Next, we introduce a PSO-based charging method. This method shares the goal of dynamic programming, but is more computationally effective. With the advanced communication technology, all information can be immediately communicated to the aggregator, which then returns a charging plan to an individual EV for the following day. The optimal control strategy will be obtained and sent to the individual vehicle as charging control signals. It is expected that most of charging occurs when the comparably lower price is reached. The driving behavior is given in Table II.

B. Particle swarm optimization

The particle swarm optimization (PSO) is a population-based heuristic global optimization technology first introduced by Kennedy and Eberhart in 1995 [22]. PSO maintains a population of particles, where each particle represents a potential solution to an optimization problem. The trajectory of each particle is adjusted dynamically according to its own flying experience and the one of other particles in the search space. Assume a D-dimensional search space $S \subset \Re^D$, and let N denote the swarm size. Each particle $i \in \mathbb{N}_N = \{1, 2, \cdots, N\}$ can be represented as an object with several characteristics. These characteristics are assigned the following symbols:

x_i: The current position of particle i;

v_i: The current velocity of particle i with the distance in a unit of time;

p_i: The personal best position of particle i, obtained through fitness evaluation (objective function $f(x_i)$); and

gb: The global best position of the whole swarm.

Then, the flight velocity of particle i for the next fitness evaluation in $d \in \mathbb{N}_D$ dimensional subspace is calculated:

$$v_{i,d}(t+1) = \omega v_{i,d}(t) + c_1 r_{1,d}[p_{i,d}(t) - x_{i,d}(t)] + c_2 r_{2,d}[gb_d(t) - x_{i,d}(t)] \quad (1)$$

where $v_i(t)$ is the particle velocity at the t^{th} iteration, $x_i(t)$ is the particle position at the t^{th} iteration. The first part of right-hand side in Eq.(1), known as the inertia component, in which, the inertia weight $\omega > 0$ controls the influence of the previous velocity vector. The second part known as the "cognitive" component, represents the personal thinking of each individual, and encourages individuals to move toward their own best position found so far. This is the personal best position of each particle achieved up to the current iteration. The third part, known as the "social" component, in which, gb is the global best position obtained so far by all individuals, represents the collaborative effect of the individuals in finding the global optimal solution, and always pulls individuals toward the global best individual found so far. In Eq.(1), the acceleration coefficients c_1 and c_2 determine the relative influence of the social and cognition components. $r_1 \sim U(0,1)$ and $r_2 \sim U(0,1)$ are elements from two uniform random sequences in the range (0,1). The new position for individuals is the addition of the position at time t and the distance that individuals will fly with the new velocity. The synchronous update of their position is thus:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

Each particle will compute their fitness value $f(x_i(t))$. Then, the personal best position of each individual is updated using the following equation:

$$p_i(t+1) = \begin{cases} p_i(t), & if \quad f(x_i(t+1)) \geq f(p_i(t)) \\ x_i(t+1), & if \quad f(x_i(t+1)) < f(p_i(t)) \end{cases} \quad (3)$$

The global best position found by any individual during all previous steps, gb is defined as:

$$gb(t+1) = \arg\min_{p_i} f(p_i(t+1)), i \in \mathbb{N}_N \quad (4)$$

C. PSO-based optimal charging methods

With the PSO algorithm the problem is addressed by considering the following discrete system that describes the battery: The number of particles is $N = 80$, the number of time intervals is $Z = 288$ and the number of iteration for each simulation is $T = 2000$.

The position $u_{i,d}$ of particle i represents the charging capacity (strategy) at time d, and $v_{i,d}$ is the flight velocity of particle i at time d.

In each iteration t ($t < T$), the charging strategy of a day represented by particle $i \in \mathbb{N}_N$ is updated by

$$u_{i,d}(t+1) = u_{i,d}(t) + v_{i,d}(t+1), d \in \mathbb{N}_Z \quad (5)$$

where $v_{i,d}(t+1)$ is calculated by equation (1).

At the same time, state variable $x_{i,d}$ representing the state of charge (SOC) of the EV battery at time d can be obtained:

$$x_{i,d} = x_{i,d-1} + u_{i,d} \quad (6)$$

The EV under our consideration is an electric propulsion system, which is characterized by an electric energy conversion chain upstream of the drive train, roughly consisting of a battery (or another electricity storage system) and an electric motor with its controller [11]. EV does not have an ICE to provide power for propulsion. Battery must be charged from an external electric network. Due to this fact, the values of $u_{i,d}$ are fixed at 0 when driving, while these values range from 0 to 1 when charged or -1 to 0 when discharged.

D_{charge} is a set of indices within the time periods when the vehicle is charging, while D_{drive} refers to the driving intervals, and $D_{discharge}$ represents the time set d within which the vehicle is pumping electricity to the grid. The summation of the numbers of elements in D_{charge}, $D_{discharge}$ and D_{drive} is $N = 288$.

$$d \in D_{charge} \cup D_{drive} \cup D_{discharge} \quad (7)$$

A specific control strategy is denoted by

$$u_d = \{u_1, u_2, u_3, ..., u_N\} \quad (8)$$

Any value of u_d has to be an element of a predefined set $U = U_{charge} \cup U_{discharge} \cup \{0\}$, known as a set of admissible decisions. The fitness function $f(u_i)$ is the total cost of a day:

$$f(u_i) := \sum_{d=1}^{N} u_{i,d} * \mu_d \quad (9)$$

μ_d refers to electricity price at time d. To minimize the cost is to minimize $f(u_i)$. The equation is listed as follows:

$$f(u) := min(f(u_i)), i \in \mathbb{N}_N \quad (10)$$

The best position u^* found by the population represents the optimal EV charging schedule strategy for a day, which has the minimum function value $f(u^*) \leq f(u)$.

IV. Simulations

We discuss three charging cases via simulations. As it is known that EVs cannot get charged during a trip, which means when $1 \leq d \leq 12$, $85 \leq d \leq 96$, and $145 \leq d \leq 156$, $u_d = 0$ according to Table II. The optional constraints are as follows:

1) The battery of EV should be fully charged at the end of the day ($x_{288} = 1$).

2) The battery capacity cannot be less than 9kWh at 15:00 ($x_{84} \geq 9/24 = 0.375$).

3) The battery capacity cannot be less than 13.5kWh at 20:00 ($x_{144} \geq 13.5/24 = 0.5625$).

The optimization result is the minimal cost of charging. The simulation program is written and executed in MATLAB and we run 100 Monte Carlo simulations.

A. Optimization of charging case I

In this case, the simulations are based on a hypothesis that charging capacity u_d ($d \in \mathbb{N}_{288}$) is the fundamental particle per stage. x_d ($d \in \mathbb{N}_{288}$) is the end charging state of each stage. The power flow in V2G is unidirectional, which means EVs can only obtain electricity power from the grid but never pump power back into the grid. The maximum charging capacity is 4kW. Therefore, the maximum charging capacity per unit stage is $4 * 5/60kWh = 1/3kWh$, and the normalized value is $u_{max} = 1/3/24 = 1/72 \approx 0.0139$. $u_{min} = 0$, $u_{min} \leq u_d \leq u_{max}$, $d \in \mathbb{N}_{288}$.

In Fig. 2, the two curves represent the state of charge x and the control variable u respectively when the charging cost is minimum. The red curves (thick one) refers to a driving state, when $1 \leq t \leq 12$, $85 \leq t \leq 96$, and $145 \leq t \leq 156$.

B. Optimization of charging case II

In this case, the simulations are based on a hypothesis that the end charging state of each stage x_d is the fundamental particle per stage. u_d is the charging capacity. The power flow in V2G can be bidirectional, which means EVs can obtain electricity power from the grid when the market price is low and also pump power back into the grid when it is high. Unlike case I, The hypothesis is that the maximum normalized charging capacity is $u_{max} = 1$, and the minimum value is $u_{min} = -1$. Apparently, battery is being charged when $0 < u_d \leq 1$; the battery is pumping power back into the grid when $-1 \leq u_d < 0$, and the battery is idle when $u_d = 0$.

In Fig. 3, the two curves represent the state of charge x and the control variable u respectively when the cost is the minimum in a day.

C. Optimization of charging case III

In this case, u_d is the fundamental particle per stage, like in case I. The power flow in V2G can be bidirectional. The hypothesis is that the maximum normalized charging capacity is $u_{max} = 1$ and the discharging capacity is double of the charging capacity, that means $u_{min} = 2 * u_{max} = 0.028$.

In Fig. 4, the two curves represent the state of charge x and the control variable u respectively when the cost is the minimum in a day.

All simulations in this paper are performed in Matlab R2008b on 2.4-GHz CPU with 4.0GB of RAM. The results of PSO-based smart charging algorithm for optimizing a 24-h interval are shown in Table III. We also obtained the results by using dynamic programming method for the case without discharging (case I). The minimum cost is 2.0493EU and the CPU time is 79.82s. For this case, the mean cost of PSO-based method is 2.0746EU (the minimum cost is 2.0412EU) and its mean CPU time is 9.0365s (the minimum CPU time is 6.2467s).

The optimal cost obtained by PSO-based algorithm is not better than that of dynamic programming on the average, however the PSO-based smart charging algorithm is much faster than dynamic programming method, saving about 90% CPU time, which is a pivotal issue for the real world application.

TABLE III
COMPARISON AMONG THREE PSO CHARGING CASES

	mean cost	minimum cost	variance of cost
Case 1	2.0746EU	2.0412EU	0.0012
Case 2	1.8337EU	1.7792EU	7.68E-04
Case 3	1.9798EU	1.9677EU	2.83E-05
	mean CPU time	minimum CPU time	variance of CPU time
Case 1	9.0365s	6.2467s	7.3924
Case 2	5.6089s	5.1486s	0.1237
Case 3	5.6199s	5.3487s	0.0143

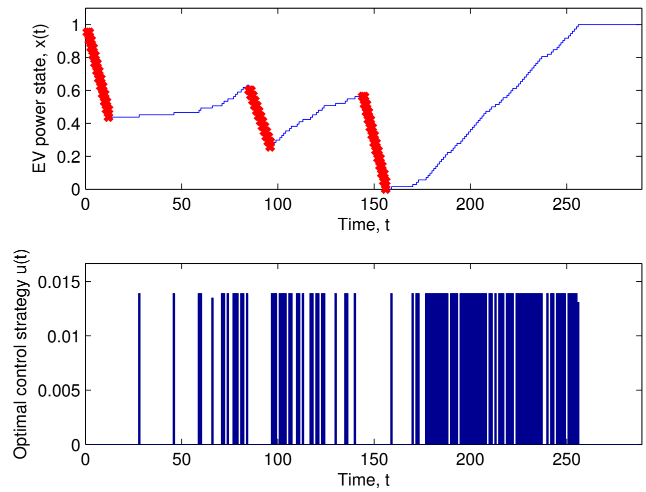

Fig. 2. Profile of case I

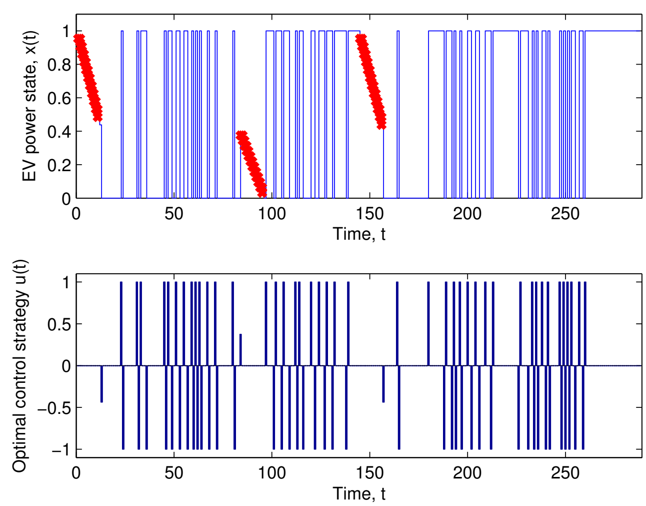

Fig. 3. Profile of case II

V. CONCLUSIONS

This paper presents a PSO-based charging method given dynamic electricity price for optimizing an EV's charging schedule. By comparing dynamic programming and PSO-based algorithms, we find the latter more efficient with much less CPU time, although the optimal cost is almost same. Comparing among the three cases, we discover that choosing

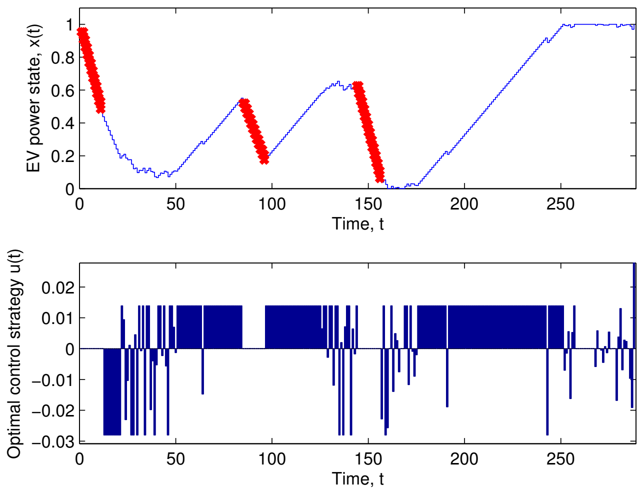

Fig. 4. Profile of case III

different parameters as particles could alter the accuracy in obtaining the lowest cost. With this method, EV is recharged during the lowest electricity price period, where is also the off peak hours. It naturally drops the possibility of grid overload during the peak load hours.

In this paper, only one EV's charging schedule has been researched. Studies of optimal control on a large number of EVs should be done, which involves high requirement on communication, and possibility that EV charging may impact the electricity price. Therefore, decentralized control architecture can be considered and electricity price forecasting models should be properly developed. Furthermore, the optimization model should be extended to account for providing regulation service given different types of EVs as well as various driving patterns. In addition, we should find a more effective method to find EV's optimal charging schedule by improving PSO or introducing a novel intelligent algorithm in the next work.

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