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PSO based Charging Scheduling for EV Parking Lots with Photovoltaic Power System

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Abstract - This paper studies the optimal charging scheduling for Electric Vehicles (EVs) in a workplace parking lot, powered by both the Photovoltaic Power (PV) system and the power grid. Due to the uncertainty and fluctuation of solar energy and the time-varying EV charging requirements, it is challenging to guarantee the economic operation of the parking lot charging station. To address this issue, we formulate the EV charging scheduling in the parking lot as a benefit maximization problem. First, by analyzing the relationship among the EV charging requirements, the charging load and the harvested solar energy, Then, we design a Dynamic Charging Scheduling Scheme (DCSS) to manage the EV charging processes, in which the Model Predictive Control (MPC) method is employed to deal with the realtime information of EV charging requirements and the solar energy. Simulation results demonstrate the effectiveness and efficiency of the designed DCSS. The extraction of maximum power from solar PV array energy and wind generation is carried out by the (PsO) scheme. –particle swarm optimization-based MPPT method to acquire rapid and maximal PV power with zero oscillation tracking.

INTRODUCTION

Climate change and extreme weather, highly related to the Greenhouse Gases (GHGs) emission, have been a critical issue facing the world. Recent data show that transportation and electricity generation, two of the major contributors to the GHGs, have an increasing trend [1]. Electric Vehicles (EVs) are a key to promote the sustainable energy development and address the air quality and climate change issues. Solar energy is green and renewable, so using Photovoltaic Power (PV) to charge EVs is promising, especially for the workplace parking lots thanks to their large space for installing the PV system and long available daytime for EVs to be charged [2]. Using solar energy solely may not satisfy the EV charging requirements due to its fluctuations and limited quantities. To satisfy the EV charging requirements, the combination of the solar energy and the power grid, namely the PV–Grid, becomes prominent [3]. The economic operation objective of the parking lot charging station is to maximize the utilization of solar energy given its low cost and smooth the load on the power grid to avoid the peak load penalty.

It is necessary to design an optimal charging scheduling scheme based on the realtime information of the EV charging requirements and the solar energy [4]. The charging scheduling problems with various goals for the charging system, powered by the power grid with or without renewable energy sources, have been widely studied [5], such as reducing the cost and guaranteeing system stability [6]–[8], maximizing total benefit [9]–[12], smoothing the charging load on the power grid [13]–[15],

To deal with the challenge, Model Predictive Control (MPC) has been used to design the charging scheduling scheme since MPC allows the current time slot to be optimized while keeping future time slots in account. In this paper, based on the realtime information at current time slot and estimated information in the upcoming time slots, a dynamic model has been proposed to update the EV charging requirements and the energy supply of the parking lot.

Literature review

According to the optimized objectives, EV charging scheduling research can be classified into two categories: cost-aware charging scheduling schemes and efficiency-aware charging scheduling schemes. Cost-aware charging scheduling schemes: Mohamed et al. in [6] designed a fuzzy controller to manage the charging processes of EVs to reduce the overall daily cost and mitigate their impact on the power grid. Tushar et al. in [7] proposed a classification scheme of EVs, such that the PV driven charging station can trade with different energy entities to reduce its total energy cost. Under the Time of Use (TOU) price, Liang et al. in [8] studied the charging/discharging scheme in Vehicleto-Grid (V2G) system and obtained a state-dependent policy to minimize the charging cost for individual EVs. Considering the battery characteristic and TOU price, Wei et al. in [9] designed an intelligent charging management mechanism to maximize the interests of both the customers and the charging operator.

Considering unpredictable EVs patterns and EV various charging preferences, Wang et al. in [10] designed a Hybrid Centralized-Decentralized (HCD) charging control scheme for EVs to coordinate the EV charging processes, such that the revenues of the whole charging system can be maximized.

HYBRID ELECTRIC VEHICLE (HEV):

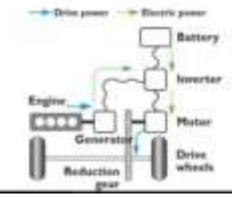
A hybrid electric vehicle (HEV) has two types of energy storage units, electricity and fuel. Electricity means that a battery (sometimes assisted by ultracaps) is used to store the energy, and that an electromotor (from now on called motor) will be used as tractionmotor.

Fuel means that a tank is required, and that an Internal Combustion Engine (ICE, from now on called engine) is used to generate mechanical power, or that a fuel cell will be used to convert fuel to electrical energy. In the latter case, traction will be performed by the electromotor only. In the first case, the vehicle will have both an engine and a motor.

- Depending on the drive train structure (how motor and engine are connected), we can distinguish between parallel, series or combined HEVs. This will be explained in paragraph1.

- Depending on the share of the electromotor to the traction power, we can distinguish between mild or micro hybrid (start-stop systems), power assist hybrid, full hybrid and plug-in hybrid. This will be explained in paragraph2.

Depending on the nature of the non electric energy source, we can distinguish between combustion (ICE), fuel cell, hydraulic or pneumatic power, and human power.



SYSTEM MODEL AND PROBLEM FORMULATION

Considering a workplace parking lot for a company, whose office hours are given, e.g., from 8:00am to 5:00pm. There are N charging piles with the AC level II charging mode in the parking lot. Each charging pile connects to the power bus of the parking lot with a centralized-controller-managed switch, such that the charging process of each EV can be managed by the controller. The power bus can be powered by both its internal PV system and the power grid. In this system, the central controller can not only collect/estimate the information of the PV system, the power grid and EVs, but also manage the charging processes of all the EVs by toggling the switches. The system model is shown in Fig. 1. Note that, the solar energy collected by the PV system can only be used by the parking lot since it cannot be fed back to the power grid due to stability and safety concerns. In the following parts, we first introduce the models of charging processes, EV charging requirements, energy supplement, and operation requirements of the parking lot. Then, we formulate a benefit maximization problem to schedule the charging processes of EVs in the parking lot.

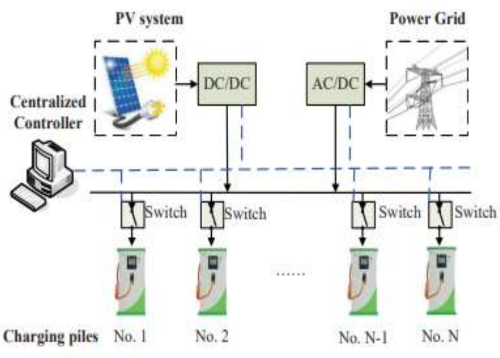


Fig. 1. The operation model of the designed system.

A. Charging Model of the Parking Lot

Let one day be a time period, which can be divided into T time slots. Let t¯ denote the current time slot and t 0 denote an upcoming time slot in the time period, respectively. Hence, t 0 > t¯ always holds in this paper. Let xi,t denote the charging decision of EV i during time slot t, t ∈ [t, T ¯], which is decided by the central controller. Here, the charging decision xi,t of EV i satisfies

$$0 \leq x_{i,t} \leq 1, \quad \forall t,$$

B.Charging Requirement Model of EVs

Generally, different EVs may have different arrival times, departure times, and charging requirements, which impact the charging decision. According to the status of EVs, we classify them into two classes: The connected EVs and the upcoming EVs2 . For each connected EV, it needs to report its arrival time, departure time and charging requirement to the central controller when it is connected to the parking lot.

$$\begin{cases} i \in \mathbb{I}(t), & \text{if } t \in [A_i, D_i]; \\ i \notin \mathbb{I}(t), & \text{otherwise.} \end{cases}$$

C.Energy Supply Model of the Parking Lot

The parking lot can be powered by both the PV system and the power grid. Let ER t denote the solar energy that is collected by the PV system, ER0 t denote the total amount of excessive harvested solar energy that cannot be scheduled to any EV by the parking lot, and EG t denote the total amount of energy from the power grid during time slot t, respectively. According to the energy conservation constraint, we have

$$\bar{E}_t = E_t^G + E_t^R - E_t^{R0},$$

where

$$E_t^{R0} \leq E_t^R, \quad \forall t.$$

Generally, for safety and reliability concerns, the power grid always issues an upper bound on its available energy for the parking lot during one time slot, denoted by E¯G. Thus, for the total energy from the power grid, we have

$$E_t^G \leq \bar{E}^G, \quad \forall t.$$

D.Operation Requirement of the Parking Lot

For the parking lot, the charging decision, {xi,t, ∀i, t}, needs satisfy the charging requirements of all the EVs. Thus, for each EV i, we have

$$R_i^O = \sum_{t=1}^{T} x_{i,t}\bar{P} = \sum_{t=A_i}^{D_i} E_{i,t},$$

since xi,t = 0 when t /∈ [Ai , Di]. It means that EV i's charging requirement should be satisfied when it is connected to the parking lot.

E.Operation Goals of the Parking Lot

In general, the main concern of the parking lot is to maximize its benefit while satisfying the charging requirements of all the EVs. Here, the benefit of the parking lot depends on the energy cost and the income. Since the collecting cost of the solar energy is low once the PV system has been installed, only the electricity cost from the power grid is considered

$$C_t^G = a_1(E_t^G)^2 + a_2E_t^G,$$

where a1EG t and a2 are load-dependent and load-independent prices respectively. Let a3 denote the income of the parking lot for charging one kWh energy to EVs. Since the total energy charged to EVs during time slot t is E¯ t, the total income of the parking lot during time slot t is a3E¯ t

$$C_T^{\bar{t}} = \sum_{t=\bar{t}}^{T} \Big(a_3\bar{E}_t - (a_1(E_t^G)^2 + a_2E_t^G) \Big).$$

F..Problem Formulation

In this paper, we aim at designing an optimal charging scheduling scheme to maximize the total benefit of the parking lot while satisfying the charging requirements of all the connected EVs. Let Xt¯ = {xi,t¯, xi,t¯+1, · · · , xi,T , ∀i} be the charging decisions from current time slot t¯ to the end of the time period T. The charging scheduling optimization problem for the parking lot can be formulated as follows:

$$\begin{aligned} \textbf{P0:}\ & \max_{\boldsymbol{X}^{\bar{t}}} C_T^{\bar{t}} \\ & \text{s.t. } \bar{E}_t \le E_t^R + \bar{E}^G, \quad \forall t \in [\bar{t}, T], \\ & \quad 0 \le x_{i,t} \le 1, \quad \forall i \in \bar{\mathbb{I}}(t), t \in [\bar{t}, T], \\ & \quad \bar{R}_i^{\bar{t}} = \sum_{t=\bar{t}}^{T} E_{i,t}, \quad \forall i. \end{aligned}$$

The objective function is to maximize the total benefit of the parking lot from current time slot t¯ to the end of the time period T. The first constraint gives the upper bound on the charging load, and the second constraint gives the available range of the charging decision. The third constraint ensures that the charging requirements of all the EVs should be satisfied.

V. SOLAR CELL

Sun based cells are intended to change over (something like a part of) accessible light into electrical energy, as their name recommends. They achieve this without depending on synthetic cycles or moving parts.

1.CHARACTERISTICS OF SOLAR CELLS

The sun based cell, which is for the most part built of PV wafers, changes over sun oriented illumination's light energy straightforwardly into voltage and flow for load, and conveys power without the utilization of an electrolytic impact. The electric energy is acquired from the PN interface of semiconductor straightforwardly; accordingly, the sun based cell is otherwise called PV cell .The same circuit of sun based cell as displayed in Figure2

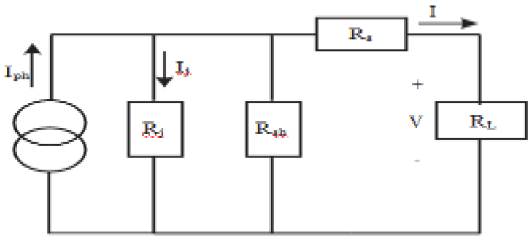


Fig2: equivalent circuit of pv array

The latest source The cell photovoltaic current is addressed by Iph, the nonlinear obstruction of the p-n intersection is addressed by Rj, and the natural shunt and series protections are addressed by Rsh and Rs, separately. Typically, the worth of Rsh is very high, though the worth of Rs is somewhat low. Therefore, the two of them may be disregarded to improve on the investigation. PV modules are comprised of PV cells that are ssembled in bigger groupings.

They are additionally interconnected in series-equal mix to shape PV clusters. The numerical model used to work on the PV exhibit is addressed by the condition

$$I = n_p I_{ph} - n_p I_{rs}\left[e^{\left(\frac{q}{kTA}\cdot\frac{V}{n_s}\right)} - 1\right]$$

Where I addresses the PV cluster yield current, V addresses the PV exhibit yield voltage, ns addresses the quantity of series cells, np addresses the quantity of equal cells, q addresses the charge of an electron, k addresses the Boltzman steady, An addresses the p-n intersection ideality factor, T addresses the cell temperature, and Irs addresses the cell invert immersion current.

VI.PARTICLE SWARM OPTIMIZATION(PSO)

Proposed in 1995 by Kennedy and Eberhart particle swarm optimization algorithm refers to an optimization approach for the public interest in society. The basic operational principle of the particle swarm is applicable for the flock of birds or fish or a group of people. While searching for food, the birds are either dispersed or go together before they locate the place where they can find the food. While the birds are searching for food from one place to another, there is always a bird that can smell the food very well, that is, the bird can observe the place where the food can be found.

PSO is a computational intelligence method that optimizes a problem by emulating a flock searching over candidate solutions (information carried by the particles) through search space. This algorithm allows all the random particles to search for the optimum solution in the search space through an iterative process. Each particle will earn their best experience while interacting with each other to share their knowledge. PSO is a faster convergence and fewer parameters to tune and easier searching in very large problem spaces.

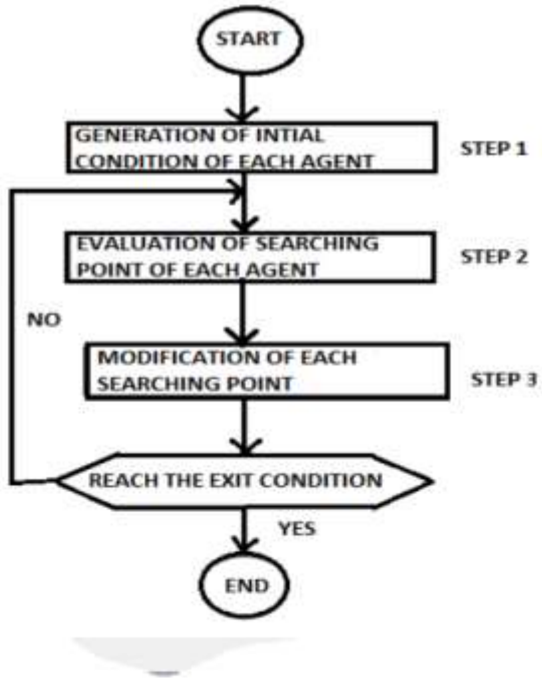


FIG3. Flow Chart of PSO

The purpose of PSO

The usual aim of the particle swarm optimization (PSO) algorithm is to solve an unconstrained minimization problem: find x* such that f(x*)<=f(x) for all d-dimensional real vectors x. The objective function f: Rd -> R is called the fitness function. .

Basic description of PSO

PSO is a swarm intelligence meta-heuristic inspired by the group behavior of animals, for example bird flocks or fish schools. Similarly to genetic algorithms (GAs), it is a population-based method, that is, it represents the state of the algorithm by a population, which is iteratively modified until a termination criterion is satisfied. In PSO algorithms, the population P={p1,…,pn} of the feasible solutions is often called a swarm. The feasible solutions p1,…,pn are called particles. The PSO method views the set R d of feasible solutions as a “space” where the particles “move”. For solving practical problems, the number of particles is usually chosen between 10 and 50

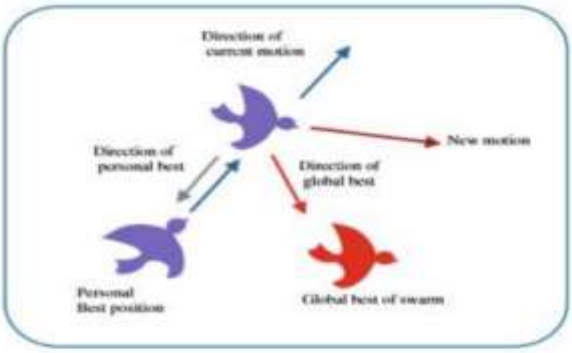


Figure 4.0 Representation of upgrading the speed of a particle

The global interest in reducing fuel consumption has led to the emergence of different types of electric vehicles like battery electric vehicle. The battery plays an important role in providing the power required by the driver. The development of greener and fuel-efficient cars can be achieved in two different ways: the development of more advanced car hardware and better control techniques. Since the latter is more profitable, more researchers pay attention to it and some papers are presented in this research.

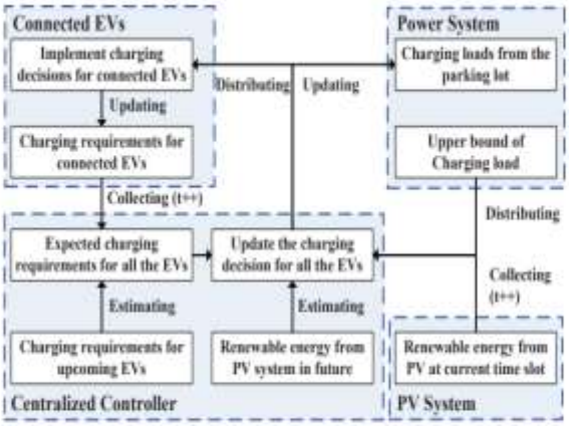


Fig. 5. The operation flow of the designed DCSS (t + + denotes the next time slots).

Due to uncertainty and fluctuation of solar energy and the time-varying EV charging requirements in future, the charging decision made at current time slot t¯ may not be the optimal charging decision for future time slots. Thus, the central controller needs to update the charging decision according to the realtime information. In this paper, MPC is adopted to deal with dynamic system parameters since it optimizes the decision in the current time slot, while tracking the the performance in future time slots. Specifically, at current time slot t¯, based on the charging decision Xt¯−1 and the realtime information from the EVs that just arrived at the parking lot, the central controller updates the charging requirements of connected EVs {Rt¯ i , ∀i ∈ I}.

Algorithm 1 The DCSS

Initialization $\bar{P}, \lambda, \mu_A, \sigma_A, \mu_L, \sigma_L, \mu_D, \sigma_D, E_D, \hat{E}_t^R, T, \bar{E}^G$

- **for** $\bar{t} = 1, 2, \cdots, T$

  1) EV i, which arrives at the parking lot during time slot $\bar{t}$, reports $\{A_i,\ D_i,\ R_i^O\}$ to the central controller;

  2) The central controller updates $\hat{E}_{\bar{t}}^R$ and $\{R_i^{\bar{t}}, i \in \mathbb{I}\}$ based on the realtime information;

  3) The central controller updates the charging decision by solving Problem **P1** distributively;

  4) The central controller implements the charging decision $\{x_{i,\bar{t}}^{\bar{t}}, \forall i \in \mathbb{I}(\bar{t})\}$ by toggling the corresponding switches;

  end for

return $\{x_{i,t}^{\mathrm{t}}, \forall i, t\}$, $\{\hat{E}_t^R, \forall t\}$, and $\{E_t^G, \forall t\}$.

SIMULATION RESULTS

A. Case Study For fair comparison,

we set the total number of EVs and their total charging requirements according to the expected values. However, different EVs may have different charging requirements. The estimated and actual data of the solar energy is shown in 6(a) and the arrival and departure times of EVs are shown in Fig. 6(b)

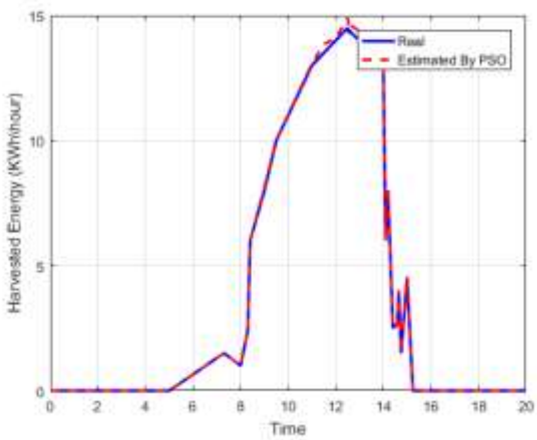
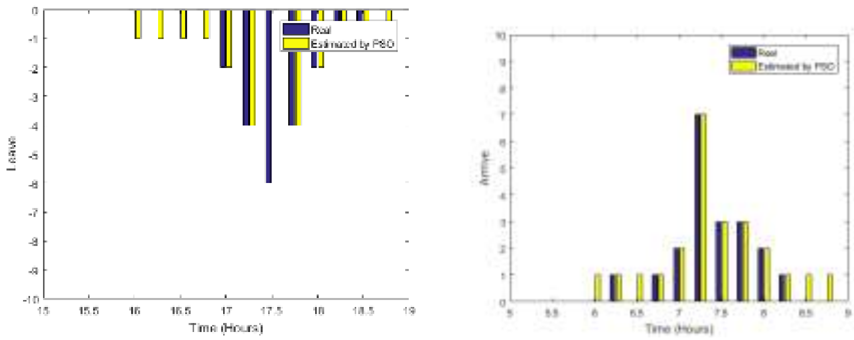
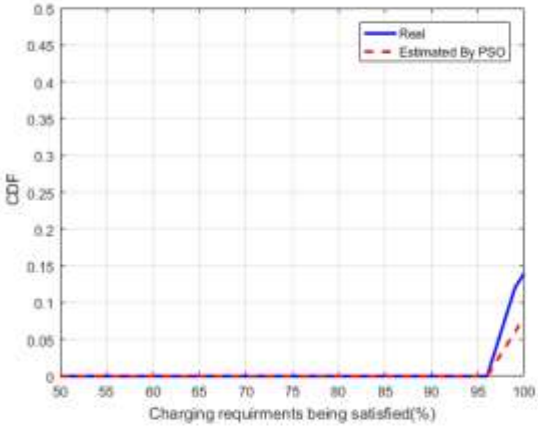


Fig. 6. Simulation setting: a) Solar energy



; b) Arrive and departure times.

Fig. 7 shows the Cumulative Distribution Function (CDF) of the charged energy to the charging requirement for the connected EVs and the benefit of the parking lot during each time slot, respectively. Since the parking lot with FIFO scheduler will charge the connected EVs to full as soon as possible, the charging requirements of all the connected EVs can be satisfied. The proposed DCSS can charge more than 85% connected EVs to full and all the connected EVs to more than 95% their charging requirements, while the Two-stage scheduler in [14] only charges 30% connected EVs to full and near 25% connected EVs under 95% their charging requirements. That is because the upper bound on the charging load on the power grid in existing work depends on the estimation of the charging requirements and the solar energy, and thus cannot guarantee the performance when the charging requirements is time-varying. From Fig. 7(b), it can



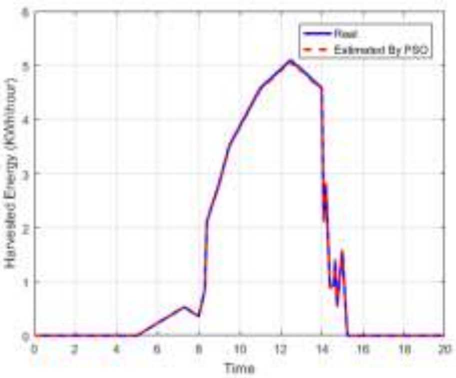


Fig. 7. The performance: a) the CDF of the charged energy to the charging requirement; b) The total benefit of the parking lot.

The total charging load of connected EVs, load on the power grid, and utilization of the solar energy are shown in Fig. 4, respectively. It can be found that both the proposed DCSS and Two-stage scheduler in [14] can reduce the peak load on the power grid significantly comparing to the FIFO scheduler. Furthermore, both of the proposed DCSS and the Two-stage schedulers can utilize the solar energy in an efficient way, while the parking lot with FIFO scheduler wasted a lot of the solar energy since all the connected EVs have been charged too soon to fully utilize the solar energy source. From Fig. 8(a), our algorithm has small fluctuations since the actual collected solar energy is different from the expected one and our algorithm adjust the scheduling scheme based on the realtime information

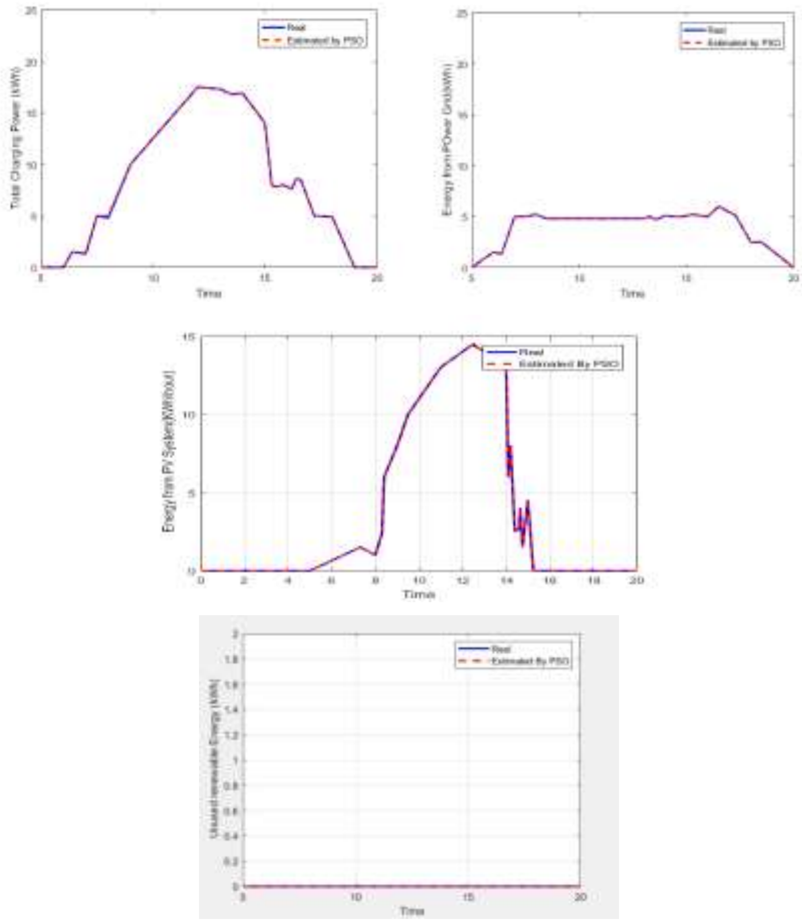


Fig.8. Simulation results: a) The total charging power of the parking lot; b) The total energy from the Power Grid; c)The total energy from the PV system; d) The total amount of unused solar energy

CONCLUSION

In this paper, we addressed the charging scheduling problem for the workplace parking lot powered by both the PV System and the power grid. Considering the realtime `information collected by the central controller and the predictive values for upcoming EVs and solar energy, we formulated a benefit maximization problem for the parking lot. Simulation results demonstrated the efficiency of the proposed charging scheduling scheme, which can increase the benefit of the parking lot significantly, while satisfying the charging requirements of all the connected EVs.

The simulation done shows the feasibility of using PSO for tuning purpose in controlling assist current of the assist motor. The result shows that PSO-mpc controller able to reduce the power consumed by the assist motor as an effort to minimize energy consumption for EV application. In future work, further improvement need to be carried out in the case of dynamic vehicle velocity.

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