paper

IEEE Publication Technology Department

***Abstract*—This document describes the most common article elements and how to use the IEEEtran class with LATEX to produce files that are suitable for submission to the Institute of Electrical and Electronics Engineers (IEEE). IEEEtran can produce conference, journal and technical note (correspondence) papers with a suitable choice of class options.**

***Index Terms*—Class, IEEEtran, LATEX, paper, style, template, typesetting.**

I. Introduction

IN order to address the dual challenges of energy and environment, the development of new energy vehicles has become a significant trend in the future transportation sector. According to China's "New Energy Vehicle Industry Development Plan (2021-2025)", it is projected that by 2035, pure electric vehicles will become the mainstream sales vehicles, and the public transportation sector will achieve comprehensive electrification. Against the backdrop of the new infrastructure construction wave, the impact of large-scale electric vehicle integration on the power grid should not be overlooked. The charging load of electric vehicles exhibits strong spatio-temporal uncertainty, and the uncoordinated integration of a significant number of electric vehicles poses challenges to the operation and control of the distribution grid. By implementing effective regulatory strategies and guidance measures to manage the charging load of electric vehicles, not only can the economic efficiency and stability of the distribution grid be enhanced, but also the grid's ability to accommodate renewable energy sources can be strengthened. In this article, the term "electric vehicles" refers specifically to pure electric vehicles, which primarily utilize electric power and produce minimal emissions of pollutants. Therefore, they can be classified as environmentally friendly transportation options. Therefore, electric vehicles present a clean transportation system choice and hold significant potential for sustainable transportation development. Moreover, electric vehicles are more easily integrated with intelligent transportation systems, thereby enhancing the efficiency of intelligent transportation services. Electric vehicles can be charged through smart charging facilities and connected to devices such as smartphones, enabling remote monitoring and management. This provides intelligent solutions for charging.Additionally, electric vehicles can engage in information sharing and collaboration with other transportation vehicles and infrastructure, aiming to achieve overall optimization and intelligent scheduling of the transportation system.By integrating with intelligent transportation systems, electric vehicles can participate in functions such as smart navigation, real-time traffic monitoring, and congestion mitigation. This enhances the efficiency and sustainability of the transportation system. Therefore, electric vehicles play a crucial role in driving the development of green intelligent transportation systems and offer new possibilities for the sustainable future of transportation.

During the 1970s, a dual algorithm was proposed to solve nonlinear variational problems. This method, based on the utilization of augmented Lagrangian functional, resulted in an effective and easily implementable algorithm. Building upon this, in 1983, D. Gabay and R. Glowinski further advanced the Alternating Direction Method of Multipliers (ADMM) and applied it to solve non-convex problems. They introduced distributed ADMM, which decomposes the original problem into two or more subproblems and gradually approaches the global optimum by iteratively solving each subproblem alternately.With the continuous advancement of computer technology, researchers have embarked on exploring the application of the ADMM (Alternating Direction Method of Multipliers) technique in distributed computing environments. In 2010, Boyd et al. identified that the alternating direction method of multipliers is highly suitable for distributed convex optimization, particularly in tackling large-scale problems arising in the fields of statistics, machine learning, and related domains.

A. 文献综述

The contributions of this article are as follows:

1)To ensure the stability of the power grid, a model was proposed to promote sparsity under ordered charging constraints. This model minimizes the total charging cost, overall load disparity, and simultaneously improves the cumulative satisfaction of all electric vehicle (EV) users.

2)We propose an improved distributed method based on the $Jacobi-proximal$ ADMM framework to solve this model. The underlying idea is to decouple the coupled constraints, decomposing the original model into a set of smaller-scale problems that can be solved in parallel. This approach not only preserves the privacy of EV users but also provides theoretical guarantees of optimality and convergence for the algorithm.

3)Compared to ADMM, the advantage of Jacobi-proximal ADMM is its faster convergence. Jacobi-proximal ADMM updates variables simultaneously at each iteration step, rather than sequentially updating them. This enables Jacobi-proximal ADMM to converge to the optimal solution more quickly. By updating variables simultaneously, Jacobi-proximal ADMM can reduce the propagation of numerical errors, which is especially important when dealing with numerically unstable problems and can provide more reliable numerical results.

II. EV Charging Control In Constrained Distribution Networks

A. Model Description

In this model, electric vehicle (EV) users upload their charging demand information to an aggregator when connecting their EVs to charging stations. Subsequently, the charging schedules for each EV are sent back to the respective EV users. The charging demand information includes the arrival time t_i^c, and the state of charge (SOC) of the vehicle when it is connected to the charging station, denoted as SOC_c. The expected SOC for each electric vehicle is referred to as SOC_d. The coordinated charging scheduling process is illustrated in Figure 1.

In this paper, we propose a novel parallel distributed algorithm based on Jacobi-Proximal ADMM to address the coordination problem of electric vehicles (EVs). This algorithm enables each EV to update its charging strategy simultaneously. The main idea is as follows: 1) Decouple the coupled constraints and decompose the original model into a set of smaller-scale subproblems, while adding proximal terms to each of the n subproblems. 2) The strategies proposed in Algorithm 1 are implemented in a parallel manner, and the global convergence of Algorithm 1 is theoretically established, along with its explicit convergence rate.We made several assumptions in our model. Firstly, electric vehicle (EV) users are sensitive to charging costs and are willing to let the aggregator arrange the charging process as long as it does not compromise their charging needs. Secondly, unforeseen events such as early departures may lead to unmet charging demands. Therefore, this study assumes that all EVs will not leave before the planned time and that EV user charging behavior exhibits typical characteristics. Numerous studies have focused on exploring the patterns of EV user charging behavior. The charging behavior of EV users can influence the effectiveness of the proposed coordinated charging scheduling model. Hence, it is necessary to consider the charging behavior characteristics of EV users in this model. Specifically, EV users connect their vehicles to the charging stations upon arriving home and disconnect them the following morning when leaving for work, resulting in the arrival time t^c and departure time t^d of EVs following a normal distribution.

$$f(t_c)=\begin{cases}\frac{1}{\sqrt{2\pi}\sigma_{t_c}}exp(-\frac{(t_c+24-\mu_{t_c})^2}{2\sigma_{t_c}^2}),\\ 0<t_c\le\mu_{t_c}-12;\\ \frac{1}{\sqrt{2\pi}\sigma_{t_c}}exp(-\frac{(t_c-\mu_{t_c})^2}{2\sigma_{t_c}^2}),\\ \mu_{t_c}-12<t_c\le 24;\end{cases} \tag{1}$$

$$f(t_{dis})=\begin{cases}\frac{1}{\sqrt{2\pi}\sigma_{t_{dis}}}exp(-\frac{(t_{dis}-\mu_{t_{dis}})^2}{2\sigma_{t_c}^2}),\\ 0<t_{dis}\le\mu_{t_{dis}}+12;\\ \frac{1}{\sqrt{2\pi}\sigma_{t_{dis}}}exp(-\frac{(t_{dis}-24-\mu_{t_{dis}})^2}{2\sigma_{t_c}^2}),\\ \mu_{t_{dis}}+12<t_{dis}\le 24;\end{cases} \tag{2}$$

whereμ_{t^c} and σ_{t^c} are the mean and variance of the probability density function of the arrival timet^c respectively;μ_{t^d}andσ_{t^d} are the mean and variance of the probability density function of the departure timet_d,Specifically,$\mu_{t_c}=18, \sigma_{t_c}=3.3, \mu_{t_d}=8$, 和$\sigma_{t_d}=3.24$.

To simplify the coordination and scheduling of the charging model, continuous time is divided into multiple time slots, where the charging status of each electric vehicle remains unchanged within a time slot. Scheduling plans are typically executed on a per-time-slot basis to improve efficiency. The scheduling time is divided into multiple time slots. In the proposed electric vehicle charging scheduling model, the entire time period is discretized into 96 time slots, with each slot having a duration of 15 minutes. The time slot for the EVi represents the arrival time and departure time, which can be calculated using the following formula(3)and(4)

$$I_i^c=[\frac{t_i^c}{\Delta T}], i=1,2,...,N. \tag{3}$$

$$I_i^d=[\frac{t_i^d}{\Delta T}], i=1,2,...,N. \tag{4}$$

whereI_i^crepresents the time slot when the$i-th$electric vehicle is connected to the charging station,while I_i^d represents the time slot when the $i-th$electric vehicle departs.t_i^c and t_i^drepresent the arrival time and scheduled departure time of the EVi,respective.$\lceil\frac{t_i^c}{\triangle t}\rceil$is the smallest positive integer greater than or equal to $\frac{t_i^c}{\triangle t}$,while$\lceil\frac{t_i^d}{\triangle t}\rceil$ is the smallest positive integer greater than or equal to$\frac{t_i^d}{\triangle t}$.

TABLE I
符号表示

$\mathcal{N}$	EV population
$\mathcal{T}$	离散时间集合
$p_{n,t}$	在t时刻第n 辆电动汽车的充电速率
$\mathcal{N}_l$	通过馈线l供电的电动汽车的集合
$\mathcal{N}_m$	在节点m 充电的电动汽车的集合
d_t	在t时刻总基本需求

B. Charging Scheduling Model Constraints

Based on the piecewise linear model, the battery dynamics can be described as follows

$$soc_{n,t+1}=soc_{n,t}+\frac{q_n^+p_{n,t}}{C_n}\Delta t-\frac{\omega_{n,t}}{q_n^-C_n}\Delta t \tag{5}$$

$$soc_n^{min}\le soc_{n,t}\le soc_n^{max} \tag{6}$$

where $q_n^+, q_n^-\in(0,1]$ represent the energy conversion efficiency for charging and discharging of electric vehicles, respectively.To extend battery life,it is recommended to set soc_n^{min} and soc_n^{max} at 15% and 90% respectively,$p_{n,t}(kW)$represents the charging rate ofEVnat time slot $t\in\mathcal{T}$,and C_n denotes EVn In each time slot, the charging rate for each electric vehicle remains constant.

Let $\boldsymbol{p}\triangleq(\boldsymbol{p}_n; n\in\mathcal{N})$ represent the charging strategy for the population of EV,The set of permissible charging strategies for EVn is denoted as $\mathcal{P}_n$, and the set of permissible charging strategies for all electric vehicles is represented by $\mathcal{P}$.

$$\mathcal{P}\triangleq\mathcal{P}_1\times\cdots\times\mathcal{P}_N \tag{7}$$

The charging strategy is the most significant factor influencing grid investment. To ensure grid safety, the following inequality holds:

$$p_n^{min} \leq p_{n,t} \leq p_n^{max} \tag{8}$$

where p_n^{min}andp_n^{max} represent the minimum and maximum charging power of EVn,respectively.By determining whether to charge electric vehicles in each time slot, coordinated charging scheduling of electric vehicles is achieved. The charging status ofEVn is as follows

$$x_{n,t} = \begin{cases} 1 & \text{if the } EV \text{ is charging} \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

The constraints satisfy the following form:

$$(1 - x_{n,t})p_{n,t} = 0 \tag{10}$$

Electric vehicles with urgent charging needs may not be able to obtain sufficient charge due to their short connection time. Therefore, the state of chargeTherefore, the state of charge (SOC)at the end of their charging period, denoted asSOC_n^{end}, may differ from the desired SOC, represented as SOC_n^d

$$SOC_n^{end} = min\{SOC_i^C + \frac{p_{n,t} \cdot \triangle t \times \eta_n}{C_n}, SOC_i^d\} \tag{11}$$

$$SOC_n^{min} \leq SOC_{n,t} \leq SOC_N^{max} \tag{12}$$

where η represents the charging energy conversion efficiency ofEVn.

C. Objective Function Optimization

When electric vehicle users require charging, they tend to prefer efficient charging and aim to complete the charging process as quickly as possible within the designated timeframe. However, such preferences can lead to charging imbalances. Charging imbalances may give rise to new demand peaks, making it necessary to adopt the peak shaving and valley filling method mentioned in the literature to balance the load of electric vehicles. The problem we are facing is how to centrally coordinate the charging of electric vehicles in order to minimize the total system cost, which serves as the objective function.

$$\mathcal{J}_0(\boldsymbol{p}) \triangleq \sum_{n \in \mathcal{N}} \left\{ f_n(p_{nt}) + g_n(\sum_{t \in \mathcal{N}} p_{nt}) + \sum_{t \in \mathcal{T}} h_n(\sum_{t \in \mathcal{T}} p_{nt}) + \|\boldsymbol{p}_n\|_0 \right\} \tag{13}$$

where each term is specifically explained as below.

1)The first term $f_n(u_{nt})$:it represents the total charging cost for the EVn. This is a price-guided sequential charging control method, which utilizes market-based control approach. The scheduling authority broadcasts price signals to the demand side and updates them periodically. The architecture diagram for this approach is illustrated in Figure 1. The total charging cost can be calculated as follows:

$$f_n(p_{n,t}) = \sum_{t \in \mathcal{T}} E_t p_{n,t} \Delta t \tag{14}$$

where E_t represents the electricity price in time period t,$p_{n,t}$denotes the charging power of electric vehicle$n$ during time period t, andΔtrefers to the time interval.

2)The second term $g_n(\sum_{t \in \mathcal{T}} p_{nt})$:This is a satisfaction function for the total energy delivered during the charging period. It represents the satisfaction function for the total energy within the charging cycle. According to equation (15), it can be observed that for electric vehicle $EV\,n \in \mathcal{N}$,the user's desire to increase the amount of electricity provided by the distribution grid as much as possible remains constant across time$t \in \mathcal{T}$until the desired energy is achieved within the expected period.

$$g_n(\sum_{t \in \mathcal{T}} p_{nt}) = -(\sum_{t \in \mathcal{T}} p_{nt} - \Gamma_n)^2. \tag{15}$$

The weight parameter$\varpi_n \in (0, \varpi_{max}]$ reflects the relative importance of reaching a full charge compared to $\mathcal{T}_n$.

3)第三项$h_n(\sum_{n \in \mathcal{N}} p_{n,t})$:It represents the ability of peak shaving and valley filling, which aims to maintain the stability of the total power in the grid. Therefore, we use the variance of the total power to reflect its stability. A smaller variance indicates a more stable grid. The total power includes the total power of electric vehicle charging and the total power of residential electricity consumption, as shown below:

$$h = (\sum_{n \in \mathcal{N}} (p_{n,t} + B_{n,t}) - \overline{p + B})^2 \tag{16}$$

The weight parameter $\omega_n \in (0, \omega^{max})$ and $\overline{p} = (\sum_{t \in \mathcal{T}} \sum_{n \in \mathcal{N}} p_{n,t})/N$。

4)The last term $\|\boldsymbol{p}\|_0$: The cardinality mentioned here refers to the total number of non-zero elements in the charging strategy bmp_n.Minimizing the l_0 norm represents considering the comfort of EV users to some extent in the overall charging process. On one hand, it aims to minimize the number of charging times and protect the battery's health. On the other hand, EV users prefer to complete their tasks as much as possible because they want to minimize interruptions or restarts of EV charging. It is generally unacceptable for most users to wait longer to complete their tasks. Therefore, by introducing a sparse charging plan, the goal of measuring user satisfaction can be unified.

This is the cardinality of the charging strategy$\boldsymbol{p_n}$,which refers to the total number of non-zero elements in $\boldsymbol{p_n}$.Minimizing the l_0 norm represents considering the comfort of EV users to a certain extent in the overall charging process. On one hand, it aims to minimize the number of charging times and protect the battery's health. On the other hand, EV users prefer to complete their tasks as much as possible because they want to minimize interruptions or restarts during EV charging. Waiting for a longer time to complete tasks is generally unacceptable for most users. Therefore, by introducing a sparse charging plan, the objective of measuring user satisfaction can be unified.

As the process of electrification in the automotive industry progresses, initially, attempts were made to model the charging strategy problem as a minimum l_2 norm problem for solving. However, the l_2 norm does not capture the sparsity required by the charging strategy of electric vehicles. In contrast, the

l_0 norm counts the number of non-zero values in a vector. Therefore, the charging strategy is modeled as a minimum l_0 norm problem to achieve shorter charging time, improved battery lifespan, and increased user satisfaction. However, the minimum l_0 norm problem is NP-hard and cannot be solved using conventional methods. Under certain conditions, the minimuml_1 problem and the minimum l_0 norm problem are equivalent, meaning that solving the minimum l_1 problem can yield the solution to the minimum l_0 problem.

Therefore, we approximate the l_0 norm with the l_1 norm. We rephrase equation(13),into the following sparse-promoting charging control model.

$$\mathcal{J}_1(\boldsymbol{p}) \triangleq \sum_{n\in\mathcal{N}} \left\{ f_n(p_{nt}) + g_n(\sum_{t\in\mathcal{N}} p_{nt}) + \sum_{t\in\mathcal{T}} h_n(\sum_{t\in\mathcal{T}} p_{nt}) + \|\boldsymbol{p}_n\|_1 \right\} \tag{17}$$

Note:

The following assumptions apply to the entire article:
(1) $h(\cdot)$ is Lipschitz continuous,for all x
(2) $g_n(\cdot)$ is non-decreasing, concave, and Lipschitz continuous,for all$n \in \mathcal{N}$ and all x.
(3)

Formulate the coordination of centralized fast charging for electric vehicles as the following optimization problem:

$$\min_{\boldsymbol{p}\in\mathcal{P}} \quad \mathcal{J}_1(\boldsymbol{p}) \tag{18}$$

III. EV Charging Framework based on $Jacobi-Proximal$ ADMM

$Jacobi-ProximalADMM$ maintains excellent properties for sparsity problems. In each iteration, this method utilizes soft thresholding operations to update variables, promoting sparsity in the solution by preserving or enhancing the sparse nature of the variables. This algorithm extends the Alternating Direction Method of Multipliers (ADMM) by decomposing the original problem into smaller subproblems, which are solved in parallel at each iteration.

To decouple the third term in the objective function of problem (18),which couples all variables $p_{n,t}\, n \in \mathcal{N}$,we introduce an auxiliary variable.

$$\boldsymbol{p}_{N+1} = (p_{N+1,1}, \cdots, p_{N+1,T})^T \in \mathbb{R}^T$$

let $p_{N+1,t} = \sum_{n=1}^{N} p_{n,t}, \forall t \in \mathcal{T}$,Thus,problem(18) can be equivalently written in the following form:

$$\min_{\boldsymbol{p}\in\mathcal{P}} \quad \mathcal{J}_1(\boldsymbol{p}) \tag{19}$$

$$\text{s.t} \quad \boldsymbol{p}_{N+1} = \sum_{n=1}^{N} \boldsymbol{p}_n \tag{20}$$

where

$$\mathcal{J}_1(\boldsymbol{p}) = \sum_{n=1}^{N+1} f_n(\boldsymbol{p}_n)$$
$$f_n(\boldsymbol{p}_n) = \sum_{t\in\mathcal{T}} E_t p_{1,t}\Delta t + (\sum_{t\in\mathcal{T}} p_{1,t} - \Gamma_1)^2 + \|\{p_{1,t}\}_{t=1}^T\|_0$$
$$f_{N+1}(\boldsymbol{p}_{N+1}) = \sum_{t\in\mathcal{T}} (p_{N+1,t} - \overline{p})^2$$

To utilize $Jacobi-Proximal\ ADMM$,we define

$$\boldsymbol{P} = \{\boldsymbol{p}_1, ..., \boldsymbol{p}_N, \boldsymbol{p}_{N+1}\}^T \in \mathcal{R}^{(N+1)\times T} \tag{21}$$

we also write $\boldsymbol{P} = (\boldsymbol{p}_1, ..., \boldsymbol{p}_T) \in \mathbb{R}^{(N+1)\times T}$, where

$$\boldsymbol{p}_t = (p_{1,t}, ..., p_{N+1,t}) \in \mathbb{R}^{N+1},\ t \in \mathcal{T}. \tag{22}$$

Define

$$\mathcal{X}_t^{(2)} = \{\boldsymbol{p}_t | \boldsymbol{p}_t \text{ 满足 } (20)\ and\ (22)\} \tag{23}$$

and

$$\mathcal{X}_t^{(2)} = \mathcal{X}_1^{(2)} \times \cdots \times \mathcal{X}_t^{(2)} \times \cdots \times \mathcal{X}_T^{(2)} \tag{24}$$

The augmented lagrangian:

$$\mathcal{L}_\rho(\boldsymbol{p}, u) = \sum_{n=1}^{N+1} f_i(\boldsymbol{p}_i) + \frac{\rho}{2}\| \sum_{i=1}^{N} p_i - p_{N+1} + u\|_2^2 \tag{25}$$

where$\rho > 0$ is the standard penalty parameter, $u$is referred to as the scaling dual variable or scaling Lagrange multiplier.The variables p and u are updated simultaneously by adding additional approximation terms. The specific update procedures are as follows: for all $n = 1, \cdots, N+1$

$$\boldsymbol{p}_n^{k+1} := \arg\min_{\boldsymbol{p}\in\mathcal{P}} f_n(\boldsymbol{p}_n) \tag{26}$$
$$+ \frac{\rho}{2}\|\boldsymbol{p}_n^k + \sum_{n\neq j} p_j^k - \boldsymbol{u}^k\|_2^2 + \frac{1}{2}\|\boldsymbol{p}_n - \boldsymbol{p}_n^k\|_\Psi^2$$

$$\boldsymbol{u}^{k+1} = \boldsymbol{u}^k + \gamma\rho(\sum_{n=1}^{N} A_n \mathbf{p}_n^{k+1} - c) \tag{27}$$

IV. 算法总结

如果迭代次数达到给定阈值$iter_{max}$ 或同时满足以下条件[*]则$DCJ-ADMM$ 满足如下:

$$\boldsymbol{r}^{k+1} = \|\boldsymbol{P}^{k+1} - \boldsymbol{Y}^{k+1}\|_F$$

$$\boldsymbol{s}^{k+1} = \|\rho(\mathbf{Y}^{k+1} - \boldsymbol{Y}^k)\|_F$$

一个合理的终止标准是原始残差和对偶残差要足够小，如下:

$$\|\boldsymbol{r}^k\|_2 \leq \varepsilon^{pri} \qquad \|\boldsymbol{s}^k\|_2 \leq \varepsilon^{dual}$$

where $\varepsilon^{pri} > 0$ 和 $\varepsilon^{dual} > 0$ are feasibility tolerances for the primal and dual feasibity conditions () and ().These tolerances can be chosen using an absolute and relative criterion,such as

$$\varepsilon^{pri} = \sqrt{N}\varepsilon^{abs} + \varepsilon^{rel} max\{\|p\|_2, \| - x\|_2\},$$
$$\varepsilon^{dual} = \sqrt{N}\varepsilon^{abs} + \varepsilon^{rel}\|\mu^k\|_2$$

where $\varepsilon^{abs} > 0$ is an absolute tolerance and $\varepsilon^{rel} > 0$ is a relative tolerance.A reasonable value for the relative stopping criterion might be 10^{-3} or 10^{-4}. A pseudo-code for the proposed Prox-JADMM is then give in Algorithm 1. 定义定理也不行

Theorem 1. 对$k \geq 1$,我们有

$$\|u^k - u^*\|_G^2 - \|u^{k+1} - u^*\|_G^2 \geq \|u^k - u^{k+1}\|_Q^2$$

其中$\|u^k - u^{k+1}\|_Q^2 := \|x^k - x^{k+1}\|_{G_x}^2 + \frac{2-\gamma}{\rho\gamma^2}\|\lambda^k - \lambda^{k+1}\|^2 + \frac{2}{\gamma}(\lambda^k - \lambda^{k+1})^T A(x^k - x^{k+1})$

Theorem 2. *应用()-()中的ADMM方法，当迭代步长$k \to \infty$时，系统收敛到最优值p^**

Proof: hello world. ■

Theorem 3. 如果$Q \succ 0$且$M_x \succeq 0$,那么$\|u^k - u^{k+1}\|_M^2 = o(1/k)$,因此， $|x^k - x^{k+1}\|_{M_x}^2 = o(1/k)$且$\|\lambda^k - \lambda^{k+1}\|^2 = o(1/k)$.

V. 结果与讨论

A. 仿真数据与设置

为了验证协调调度模型的有效性，进行了基于$Jacobi-ProximalADMM$方法的仿真实验。实验中的输入数据根据概率密度函数随机生成，模拟真实电动汽车充电情况。然而，为了简单起见，必须建立一些假设。

首先，采用不同数量的电动汽车(100辆、200 辆、300 辆)进行对比实验

其次，SOC_i^{con}表示电动汽车的连续均匀分布，取值范围为0.1到0.3。SOC_i^{min} 表示电动汽车的最小充电状态，服从0.4 到0.6 之间的均匀分布，而$SOC_i^m ax$表示电动汽车的最大充电状态，服从0.8 到1.0 之间的均匀分布。此外，所有电动汽车电池的容量Cap_{EV}^{bat} 设定为30kWh。

最后，根据用电规律对基本负荷数据进行了模拟.仿真结果如图2所示。分时电价如图1 所示，假设所有电动汽车的$Cap_{battery}$ 值为30kwh[*], 电网的基本负荷如图2所示。考虑到用户下班前充电一定电量的意愿,本仿真中电动汽车充电协调的时间范围T正态分布考虑.

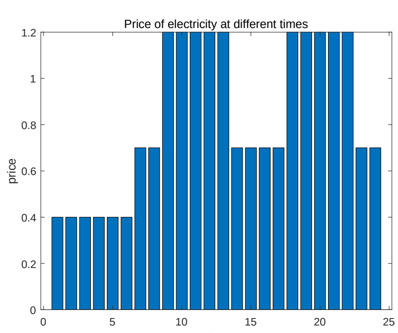

Fig. 1. TOU electricity price[?]

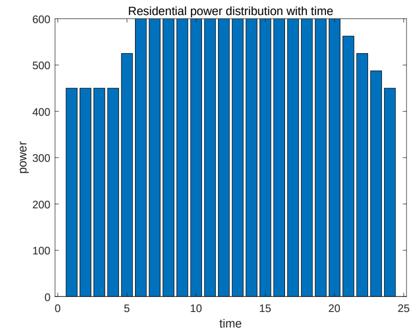

Fig. 2. 一天的典型基本负荷曲线待修改

首先，我们将(u^0, z^0, v^0)都初始化为0. 在初始迭代步骤中，假设$k = 1$, 我们对所有$n \in \mathcal{N}$ 使用算法1实现u_n^1, 根据图4 的说明,它会在几次迭代中收敛。然后，基于收集到的充电策略*********通过(*)这个

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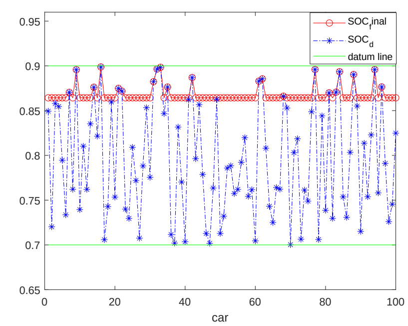

Fig. 3. 100辆EV离开时的SOC

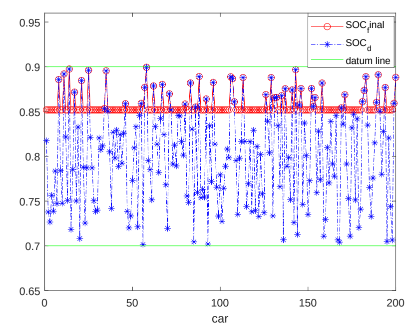

Fig. 4. 200辆EV离开时的SOC

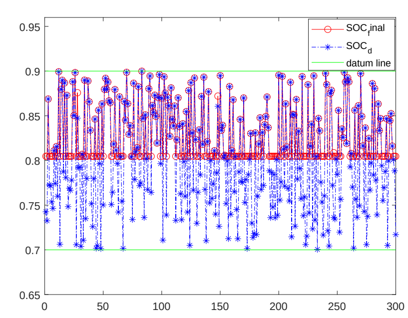

Fig. 5. 300辆EV离开时的SOC

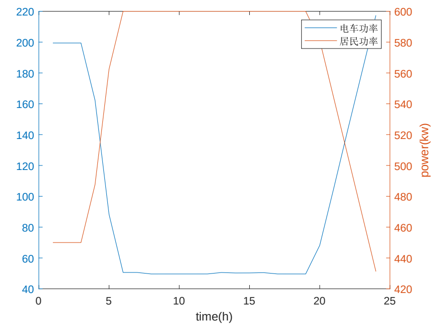

Fig. 6. 100辆EV的削峰填谷

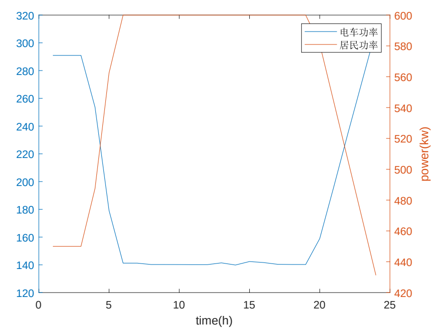

Fig. 7. 200辆EV的削峰填谷

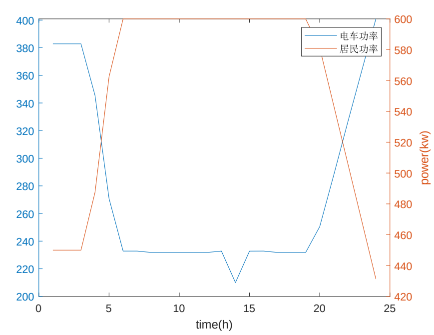

Fig. 8. 300辆EV的削峰填谷

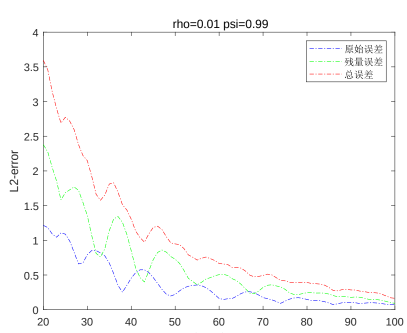

Fig. 9. 100辆EV的原始和对偶误差

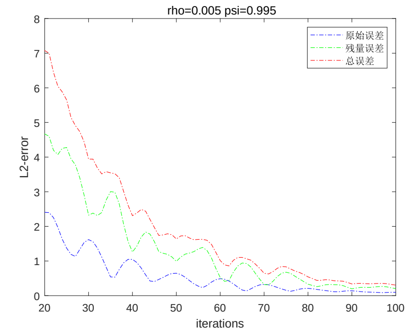

Fig. 10. 200辆EV的原始和对偶误差

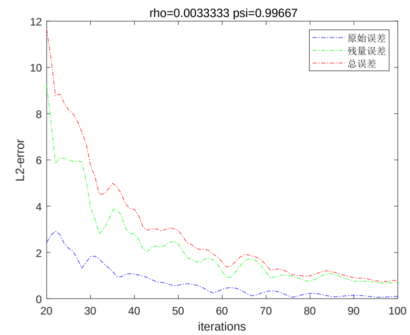

Fig. 11. 300辆EV的原始和对偶误差