Layered and Distributed Charge Load Dispatch of Considerable Electric Vehicles

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***Abstract*—Cooperation between controllable loads such as electrical vehicles (EVs) and wind power is regarded as a promising way to promote the integration of wind power. A novel layered and distributed charging load dispatch mechanism is proposed for the control of thousands of EVs in this paper. Based on the Lagrangian Relaxation and Auxiliary Problem Principle, the dispatch framework is developed, consisting of layers of system operator, generation units/EV aggregators, and EVs, and the cooperation between the generation and EVs is considered. Furthermore, the necessity of EV aggregators is analyzed, and the function of them is stressed. Compared with existing distributed methods, the proposed method is proper for large populations of EVs and gains an advantage in reducing generation cost directly. In addition, it is with a wider application scope such as problems with coupled constraints. The case study on IEEE-RTS verifies the method is feasible and valid and the charge load dispatch based on it reduces generation cost and wind power spillage.**

***Index Terms*—Auxiliary Problem Principle, electric vehicle (EV) aggregators, EV charge control, Lagrangian Relaxation, layered and distributed charge load dispatch.**

NOMENCLATURE

A. Index

gi	Index of generators.
wi	Index of wind farms.
ei	Index of electric vehicles.
ai	Index of electric vehicle aggregator.
t	Index of timeslots.
s	Index of wind power scenario.
k	Index of iteration number, and variables with superscript k means corresponding results in the kth iteration.

B. Variables, Parameters and Functions

$card()$	Number of elements in a set.
$csignal_{ai}^{k}$	Charge control signals in the kth iteration.
$disp_{ei,\max}$	EV maximal discharge power.
$disp_{ei,t}$	EV discharge power.
$E_{ei,\min}$	Lower limit of EV stored energy.
$E_{ei,\max}$	EV storage capacity.
$E_{ei,t}$	EV stored energy.
$Econs_{ei,t}$	Energy consumed in trips of an EV.
$f_{gi}()$	Cost curve of a generator.
F	Objective function.
$p_{gi,t}$	Conventional generation power output.
$p_{gi,t,s}$	Conventional generation power output considering multi-scenario wind power.
$P_{L,t}$	Conventional or fixed load power.
$pch_{ei,\max}$	EV maximal charge power.
$pch_{ei,t}$	EV charge power.
$pdr_{gi,t}$	Downward reserve provided by a generator.
$pur_{gi,t}$	Upward reserve provided by a generator.
$prob_s$	Probability of wind power scenario.
Rd_t, Ru_t	Downward/upward reserve demand of the grid.
$rpch_{ei,t}$	EV net power connected to the grid.
$RW_{wi,t,s}$	Dispatched wind power.
S_{gi}	Startup/shutdown cost of a generator.
T	Total number of timeslots in a dispatch period.
$u_{ei,t}$	EV plugged state indicator, 1 means plugged-in and 0 means unplugged-in.
$u_{gi,t}$	Unit state indicator, 1 means on and 0 means off.
$W_{wi,t,s}$	Simulated wind power.
$\lambda_t, \mu d_t, \mu u_t$	Dual multiplier of the balance, downward reserve and upward reserve constraint.
$\lambda_{t,s}$	Dual multiplier of the balance constraint considering multi-scenario wind power.
$\eta_{ei,c}, \eta_{ei,dc}$	Charge/discharge efficiency of EV.
Δ_{gi}	Permissible power adjustment of a generator.
Δt	Timeslot duration, 1 h in this paper.
c, ε, b	Parameters needed in ALR.
$\varepsilon_1, \varepsilon_{2,ai}$	Parameters needed in the modified ALR.

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I. Introduction

Electric vehicles (EVs) gain great advantages over conventional cars in reducing emissions and alleviating the dependence on fossil fuel. The combination of transport electrification and renewable generation is an efficient way to control carbon emission and gain the attention of governments, industry, and the masses [1]. Popularized EVs provide considerable controllable resources for power systems as well as raising energy demand, since the EVs are free from trips for 96% of the time on average [2]. EVs, equipped with batteries, can be charged at a flexible time and power rate. Moreover, they can discharge to support the grid operations by the vehicle-to-grid (V2G) technique [3]. Research dated from the 1980s has shown that charge control improves supporting capacity of the grid for EVs and avoids power shortage [4]. Recently, many works have shown that charge control including V2G cannot only offer many kinds of auxiliary services, such as reserve and regulation [2], but also stabilize the grid and promote the integration of wind power [3].

Many studies have been devoted to forming feasible charge schemes and exploiting benefits of EVs [5]–[11]. Charge control strategies have been studied and discussed on different levels such as a single EV [5], EV parks [6], distribution grids [7], [8], and regional power systems [9]–[11], which can be put into two categories: centralized and decentralized (or distributed). For regional grids and some large-scale distribution networks, it is difficult for centralized methods to provide feasible charge schemes because the number of EVs can be enormous and the constraints of EVs are complicated, which is beyond their handing ability and simplifications of different extents are adopted [9]–[11].

The distributed framework appears to be more proper for the charge control of vast EVs. Compared with the centralized method, the decisions are made by a single EV, and only its own constraints need to be included. A more sophisticated model can be developed for every EV, and their constraints will not be violated. The coordination is realized by an iterative process rather than a complex and large-scale optimization problem. In addition, users are just requested to provide charge/discharge curves to the system operators rather than technical parameters of EV and trip plans in the distributed framework, which gives it an advantage over centralized models on the privacy protection.

The key of distributed charge control lies in coordinating all EVs to realize one objective such as optimal operation of the grid. Some works have made their efforts, such as the method in [12] based on Game Theory and the method in [13] based on convex analysis. The former is limited to valley-filling of load curves by pure charge control (discharge of EVs is not included), while the latter is extended to track a given load profile. Unfortunately, the latter is related to the number of EVs, failing to dispose of charge control problems in grids with vast EVs. The limitations of the existing methods are summarized as follows. First, they fail to optimize the generation cost directly, in which operators are more interested. Second, they just apply to problems with only separated constraints and no coupled ones such as the power balance. The existing methods can only coordinate EVs and fail to coordinate EVs with generation units and the grid in essence.

In this paper, based on the modified Lagrangian Relaxation (LR), we propose a novel layered and distributed charge control framework to minimize generation cost and coordinate EVs and generation units. The contributions of this paper include the following. Firstly, we propose a distributed framework by means of LR, in which the generation cost is optimized directly and coupled constraints are included. Secondly, modification of augmented LR is adopted to improve the quality of LR and based on it, the layered and distributed framework is proposed. The framework is constituted by the system operator (SO) layer, the generation unit/EV aggregator layer and EV layer. The cooperation between EVs and units is realized on the top and middle layers while the cooperation among EVs on the middle and bottom layer. The necessity and function of EV aggregators are elaborated and expressed based on the algorithm analysis. Finally, the framework is extended to dispose of stochastic wind power according to the stochastic dual theory and the synergistic dispatch between wind power and EVs is realized.

The remainder of this paper is organized as follows. The charge control problem is formed in Section II and is decomposed by LR in Section III. Section IV proposes and discusses the layered and distributed framework, and Section V extends it to consider stochastic wind power. Cases studies and conclusions are presented in Sections VI and VII respectively.

II. Problem Formulation

Generation cost is an important economic index in power system operation and reflects the social benefits of electricity supply when user benefits are assumed to be constant. The objective function of charge load dispatch is to minimize the generation cost directly. The generation consists of fuel cost and startup/shutdown cost, which can be minimized in

$$\min F = \sum_{t=1}^{T} \sum_{gi} [f_{gi}(p_{gi,t}) + s_{gi} u_{gi,t}(1 - u_{gi,t-1})]. \quad (1)$$

The fuel function f_{gi} is usually quadratic. For simplification, s_{gi} is assumed to be constant. Related constraints are as follows.

A. Grid Constraints

$$\sum_{gi} p_{gi,t} - P_{L,t} - \sum_{ei} rpch_{ei,t} = 0 \quad (2)$$

$$\sum_{gi} pur_{gi,t} - Ru_t = 0 \quad (3)$$

$$\sum_{gi} pdr_{gi,t} - Rd_t = 0. \quad (4)$$

The power balance constraint is presented in (2) while the reserve constraints are presented in (3) and (4). The upward and downward reserve demand is determined by the load uncertainty, unit outage, and volatility of renewable power which appears to be more and more important for wind power development. It is not considered here that EVs provide reserve. On the other hand, EVs are assumed not to call for reserve either. The network constraints are not included to concentrate on the basic concept and algorithm. The grid constraints are coupled and related to many elements in the grid.

B. EV and Conventional Units Constraints

The primal use of EVs is to travel. EVs can be taken as storage depending on user trips. An EV should meet its technical and trip constraints as follows:

$$0 \le pch_{ei,t} \le pch_{ei,\max} u_{ei,t} \tag{5}$$

$$0 \le disp_{ei,t} \le disp_{ei,\max} u_{ei,t} \tag{6}$$

$$E_{ei,\min} \le E_{ei,t} \le E_{ei,\max} \tag{7}$$

$$\begin{aligned} E_{ei,t} = {} & E_{ei,t-1} + pch_{ei,t}\eta_{ei,c}\Delta t \\ & - disp_{ei,t}/\eta_{ei,dc}\Delta t - Econs_{ei,t} \end{aligned} \tag{8}$$

$$rpch_{ei,t} = pch_{ei,t} - disp_{ei,t} \tag{9}$$

Constraints (5) and (6) correspond to the maximal charge and discharge power respectively, which is determined by power capacity of batteries and power electronics charge equipment. When $u_{ei,t}$ equals 0, the EVs is not plugged in, and the charge/discharge power is limited to 0. The energy limits are expressed in (7). The stored energy should not be beyond the storage capacity of batteries. On the other hand, given the adverse effects of deep discharge on battery lifetime, the stored energy should not be below some level $E_{ei,\min}$, which is often set to be 20% of the storage capacity. Constraints (8) present the energy balance in batteries, which is related to both the charge/discharge process and user trips. The energy demand of user trips can be met naturally with Constraints (7) and (8) considered. The power connected to the grid is calculated in (9). Given the charge/discharge efficiency, the constraints are redundant that EVs cannot charge and discharge simultaneously, when the objective function of charge control is minimizing charge cost, just like the EV subproblem in Section III.

The constraints of conventional units are also included, which are similar to those in unit commitment (UC) problems including the maximal/minimal power output, minimal on/off time, ramping rate and so on [14]–[16]. They are not presented here for simplification.

The constraints on EVs and units are separated and only related to themselves, called single constraints in this paper.

The dispatch problem is featured by the following. First, the objective function is additive and separable. Second, the constraints consist of the single and coupled ones. The number of the single is related to that of EVs and units while the number of the coupled is relatively limited.

III. Distributed Framework Based on LR

A. Decomposition

The problem scale explodes with the EV number increasing. LR is a widely used decomposition method to dispose of large-scale optimization problems [17] and has been successfully used to solve UC problems in power systems [14]–[16]. It gains a great advantage over other methods on less sensibility to the problem scale. Here, LR is adopted to realize the distributed charge control and cooperation between EVs and generation units.

The coupled constraints are relaxed by the corresponding dual multipliers λ_t, μu_t, and μd_t, and we can get the dual problem as shown in

$$\begin{aligned} L = F & + \sum_{t=1}^{T} \lambda_t \left(P_{L,t} + \sum_{ei} rpch_{ei,t} - \sum_{gi} p_{gi,t} \right) \\ & + \sum_{t=1}^{T} \mu d_t \left(Rd_t - \sum_{gi} pdr_{gi,t} \right) \\ & + \sum_{t=1}^{T} \mu u_t \left(Ru_t - \sum_{gi} pur_{gi,t} \right) \end{aligned} \tag{10}$$

which can be decomposed as single problems of units and EVs; see the following equations:

$$\begin{aligned} \min L_{gi} = {} & \sum_{t=1}^{T} \left[f(p_{gi,t}) + s_{gi} u_{gi,t} (1 - u_{gi,t-1}) \right] \\ & - \sum_{t=1}^{T} (\lambda_t p_{gi,t} + \mu d_t pdr_{gi,t} + \mu u_t pur_{gi,t}) \end{aligned} \tag{11}$$

$$\min L_{ei} = \sum_{t=1}^{T} \lambda_t rpch_{ei,t}. \tag{12}$$

The corresponding single constraints are not displayed, which can be found in Section II.

The dual multipliers reflect the power supply and demand situations. λ_t, μu_t, and μd_t correspond to the real-time marginal price (or cost) of the electricity, upward reserve, and downward reserve. The single problems can be regarded as the generation cost minimization problem of units or charge cost minimization problem of EVs respectively. In UC, units are coordinated via the adjustment and update of multipliers. Here, the cooperation between EVs and units are realized by the similar idea.

B. Distributed Framework

According to the procedure of LR [14]–[17], the distributed charge control framework can be built as the following steps.

Step 1) SO releases original dual multipliers (or prices) as dispatch signals to generation units and EVs.

Step 2) In response to the released signals, EVs and generation units optimize their own charge/discharge process and operation by solving the single problems and submit their cost and power curve to SO.

Step 3) SO calculate the dual objective function L^* and corresponding primal objective function J^* by the submitted cost and load curves respectively.

Step 4) The relative dual gap (*rdg*) is calculated by SO as

$$rdg = \frac{J^* - L^*}{L^*} \times 100\%. \tag{13}$$

Step 5) If *rdg* is below the threshold, go to step 5); otherwise, update the dispatch signals and go to step 1).

Step 6) The EV charge power is optimal. The unit power can be determined by the feasible solution construction.

The EV decisions are made distributed via the decomposition. Only the charge/discharge curves and dual multipliers need to be transmitted between SO and EVs. The EV technical parameters and user trip plans are concealed. The privacy of users is protected. Due to the large number of EVs, there is enormous communication and summation burden on SO. Thus EV aggregators can be introduced as an intermediary agent. Aggregators receive dispatch signals of SO and transmit them to EVs. They also collect and sum the charge/discharge curve and cost of EVs attached to them and submit to SO. A tree organization of multilayer EV aggregators can be developed. This framework is regarded as a distributed framework rather than a layered and distributed framework, because the function of the aggregators is limited to the information transmission.

IV. Layered and Distributed Framework

A. Modifications

As shown in (12), the EV subproblems are linear, the optimum of which are obtained at the extreme points. The optimizing region of EV charge control is lessened because of the LR decomposition. Moreover, the linear programming is not a strict convex problem, which may cause oscillations and a low convergent speed in iterations [16]. Here, the augmented LR is adopted by adding the square of coupled constraints to the Lagrange function. Taking (2) as an example, the so-called Augmented Lagrange (AL) function can be obtained as

$$AL = L + \frac{c}{2}\sum_{t=1}^{T}\left(P_{L,t} + \sum_{ei} rpch_{ei,t} - \sum_{gi} p_{gi,t}\right)^2. \quad (14)$$

Despite an improvement on the problem behavior, the introduction of square items destroys the additive separability of the objective function. According to the Auxiliary Problem Principle (APP) [18], *AL* can be linearized in the neighborhood of the solution in the last iteration. Thus, we can obtain

$$\begin{aligned} AL = {} & L+\frac{1}{2\varepsilon}\sum_{t=1}^{T}\left[\sum_{gi}\left(p_{gi,t}-p_{gi.t}^{k}\right)^2+\sum_{ei}\left(rpch_{ei,t}-rpch_{ei,t}^{k}\right)^2\right] \\ & + c\sum_{t=1}^{T}\left(P_{L,t}+\sum_{ei} rpch_{ei,t}-\sum_{gi} p_{gi,t}\right) \\ & \times\left(P_{L,t}-\sum_{ei} rpch_{ei,t}^{k}-\sum_{gi} p_{gi,t}^{k}\right). \end{aligned} \quad (15)$$

The linearized problem is separable, and the subproblems in the $(k+1)$th iteration are related to the results in the kth step. The EV subproblem is quadric, the convexity of which is strengthened and optimizing region enlarged. In addition, severe oscillations can be avoided.

According to related conclusions in [18], the algorithm developed by APP is convergent for convex problems, when the condition in

$$0 < \varepsilon < \frac{1}{c(card(gi) + card(ei))} \quad (16)$$

is met. The charge control problem is a near convex problem and the similar convergent conditions are needed.

In the charge control problem, the number of EVs is so huge that ε must be very small and *AL* and the subproblems are ill-conditioned. Thus, we introduce the charge/discharge power of EV aggregators by the following equations:

$$arpch_{ai,t} - \sum_{ei\in ai} rpch_{ei,t} = 0 \quad (17)$$

$$\sum_{gi} p_{gi,t} - P_{L,t} - \sum_{ai} arpch_{ai,t} = 0 \quad (18)$$

where $ei \in ai$ stands for the EVs attached to aggregator ai. Since (17) and (18) are equivalent to (2), their dual multipliers are at the same value. Replacing (2) with (17) and (18) in the *AL*, according to APP, we can obtain the modified subproblems of generators, EV aggregators and EVs, presented as

$$\begin{aligned} MAL_{gi} = {} & L_{gi}+\frac{1}{2\varepsilon_1}\sum_{t=1}^{T}\left(p_{gi,t}-p_{gi,t}^{k}\right)^2 \\ & - c\sum_{t=1}^{T} p_{gi,t}\left(P_{L,t}+\sum_{ai} arpch_{ai,t}^{k}-\sum_{gi} p_{gi,t}^{k}\right) \end{aligned} \quad (19)$$

$$\begin{aligned} MAL_{ai} = {} & c\sum_{t=1}^{T} arpch_{ai,t}\left(P_{L,t}+\sum_{ai} arpch_{ai,t}^{k}-\sum_{gi} p_{gi,t}^{k}\right) \\ & + \left(\frac{1}{2\varepsilon_1}+\frac{1}{2\varepsilon_{2,ai}}\right)\sum_{t=1}^{T}\left(arpch_{ai,t}-arpch_{ai,t}^{k}\right)^2 \end{aligned} \quad (20)$$

$$\begin{aligned} MAL_{ei} = {} & L_{ei}+\frac{1}{2\varepsilon_{2,ai}}\sum_{t=1}^{T}\left(rpch_{ei,t}-rpch_{ei,t}^{k}\right)^2 \\ & + c\sum_{t=1}^{T} rpch_{ei,t}\left(\sum_{ei\in ai} rpch_{ei,t}^{k}-csignal_{ai}^{k}\right). \end{aligned} \quad (21)$$

During the control process, problems (19) and (20) are solved first. The charge/discharge power of aggregators can be obtained by solving (20), which is released as charge control signals to EVs attached to them. Then EVs schedule their own charge/discharge process by solving problem (21). The EV charge/discharge power is summed by aggregators, based on which problems in next iteration are linearized and solved.

Thanks to the introduction of aggregator subproblems, the convergent conditions are modified as follows:

$$0 < \varepsilon_1 < \frac{1}{c(card(gi) + card(ai))} \quad (22)$$

$$0 < \varepsilon_{2,ai} < \frac{1}{c(card(ei|ei \in ai) + 1)}. \quad (23)$$

The tiny ε_1 and $\varepsilon_{2,ai}$ and ill-conditioned subproblems can be avoided via the proper configuration of EV aggregators. In essence, the ill-conditioned problems result from that generation units and EVs are optimized simultaneously on the same level. The former is of large capacity but small number while the latter is of small power scale but large number. With aggregators introduced, they are segregated and optimized on the different layers. The power scale of aggregators can be set similar to the capacity of units. As required in (22)–(23), both the number of aggregators and the number of EVs belonging to an aggregator cannot be very big. Multilayer aggregators can be introduced, and similar algorithms can be developed following the proposed method. Geographically close EVs can be allocated to one aggregator for convenience

B. Feasible Solution Construction

For nonconvex programming, the solution of the dual problem is usually an infeasible solution of the primal problem [17]. In UC, the feasible solution construction can be summarized as follows: 1) the dual solution of integer variables are assumed to be optimal and the primal problem is reduced to an economic dispatch problem; 2) the power output of units is determined by solving the economic dispatch problem; and 3) if the economic dispatch problem is infeasible, heuristics will be included to modify the integer solution. The construction of feasible solutions is carried out in every iteration [19].

Given the large number of EVs, it is impossible to determine the charge power of EVs in the economic dispatch problem. Thus, we assume the charge/discharge power to be optimal, and the primal problem is reduced to a generation schedule problem, the feasible solutions of which can be constructed by the method adopted in UC. It has little influence on the quality of charge power solutions, the optimizing region of which is enlarged by the introduction of square items.

In addition, penalty functions can be employed to restrain the discrepancy between the supply and demand of power and reserve, which guarantee the feasibility of the reduced primal problem. By this way, we can avoid constructing feasible solutions in every iteration and the calculation can be simplified. When the iteration is converged, the feasible solution can be constructed via the existing methods.

C. Framework Overview and Implementation

Sophisticated aggregators are necessary to avoid the ill-conditioned problems, and their functions are induced by related algorithm analysis. Based on it, we propose the layered and distributed charge load dispatch framework. Here related work in Part A is re-organized to elaborate the framework and the dispatch process.

The framework usually consists of three layers, SO Layer (L1), generation unit/main EV aggregator Layer (L2) and EV Layer (L3), as shown in Fig. 1. To some large-scale grid, there can be multiple layers of subaggregators between the main ones and EVs, which form a tree-like charge load dispatch system. The levels are coordinated as follows.

In L1, the cooperation of the whole grid is carried out by SO. It releases dispatch signals (dual multipliers or marginal price) to generators and EV aggregators, and keeps adjusting and updating the signals according to the response of units and aggregators until the iteration is converged.

In L2, units and aggregators schedule their operation in response to dispatch signals. The on/off state and power output are decided by units and submitted to the SO. The aggregators cooperate with units via SO and coordinate the charge/discharge process of EVs attached to them, as an intermediary between EVs and SO. Given the dispatch signals, aggregators determine their charge/discharge power and transmit them to EVs as charge control signals in along with the dispatch signals. The aggregators can be configured according to their geographic location and EVs in the same zone can be divided into the identical aggregator.

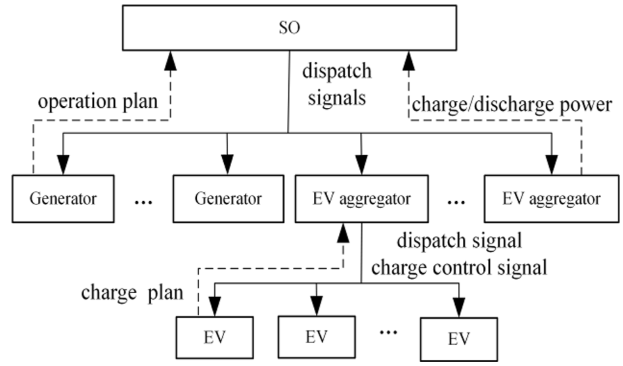

Fig. 1. Procedure of the layered and distributed framework.

In L3, the EV charge/discharge power is optimized within related constraints based on the dispatch signals from SO and charge control signals from the superior aggregator. In addition, EVs should submit their charge plan and cost to their superior aggregator.

With the related algorithm shown in Fig. 2, the proposed dispatch process can be summarized in the following steps.

- Step 1) Before a new dispatching period (usually 1 day) starts, SO release a set of the initial dispatch signals.
- Step 2) According to the dispatch signals, the generators formulate their own optimal operation plan and submit their plan to SO;
- Step 3) According to the dispatch signals, the aggregators schedule their charge/discharge process, produce the charge control signals, and transmit them to affiliated EVs in along with the dispatch signals and the charge/discharge power sum in the last iteration;
- Step 4) EVs optimize their own charge/discharge process in response to the dispatch signals and charge control signals and submit their charge/discharge curves to superior aggregators;
- Step 5) Aggregators sum the charge/discharge power of EVs attached to them and submit to SO;
- Step 6) According to the information submitted by the generators and aggregators, the relative dual gap *rdg* is calculated and the convergent condition is checked;
- Step 7) If convergent, the dispatch process is ended and the dispatch schedule is fixed; Otherwise, the dispatch signals is updated and released by SO and go to step 2).

As shown, two kinds of signals are included in the charge load dispatch: the dispatch signals released by the SO which take effect across the grid and the charge control signals formed by every aggregator which work within the aggregators. To EVs, the former contain price or marginal cost information of the grid at different times and guide them to charge when the price is lower and discharge when the price is higher, while the latter

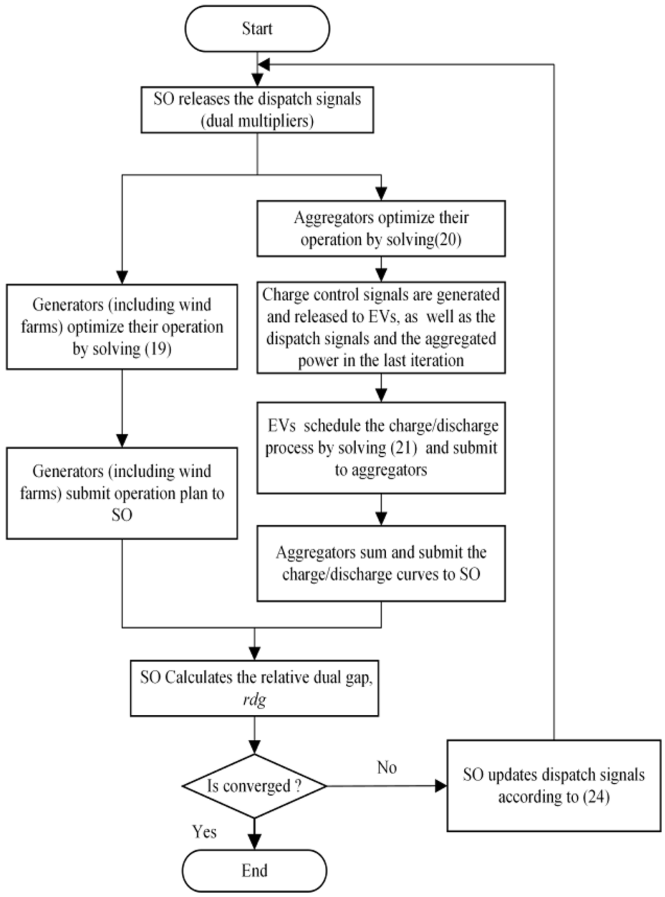

Fig. 2. Procedure of the layered and distributed framework.

reflect the charge/discharge power of aggregators in the last iteration and are adopted to avoid oscillations of EV charge schedules. In the framework, the charge control signals are obtained by solve the aggregator sub-problems while the dispatch signals or dual multipliers in other words, are updated by SO according to power output of units and charge/discharge power of EVs in each iterations. Similar to UC problems, many methods can be used to update multipliers, here the subgradient method is adopted [14]–[16]:

$$\lambda_t^{k+1} = \lambda_t^k + b\left(P_{L,t} - \sum_{gi} p_{gi,t}^k + \sum_{ei} rpch_{ei,t}^k\right). \tag{24}$$

As proved in [18], the algorithm is convergent if b lies in (0,2c).

Compared with that in the distributed framework, the function of EV aggregators is strengthened and stressed. Aggregators are requested to form local charge control signals and take an active part in the grid cooperation as well as transmit information between EVs and SO. Small-capacity but large-number EVs are aggregated to provide controllable resources for the grid, like generation units.

Despite the introduction of the aggregators, there is only an iteration loop needed in the framework. The time consumed is determined by the iteration number and time consumed in every iteration. Compared with solving UC by LR or the augmented LR, the proposed framework only spends extra time on the communication delay in every iteration, since the EV and aggregator subproblems are much simpler than the generator subproblem. The communication delay is related to the device in the smart grid, but the information to transmit is very limited, just including the dispatch signals, the charge control signals and the charge/discharge schedule. On the other hand, the iteration number is related to the grid property and selection of parameters. Further work is needed on the parameter selection and optimization to accelerate the iteration. In addition, the iteration number can be an alternative stopping criterion.

The proposed framework is similar to the hierarchical dispatch mechanism now used in China and many other countries. Different from the existing open-loop one, it introduces information feedback of EV/unit behavior. Thanks to the development of smart grids, the framework can be implemented by constructing multi-agent systems including SO, aggregator and EV agents [20].

V. Extensions to Including Wind Power

A. Model Considering Wind Power

Different from conventional generation, wind power is stochastic and intermittent. Similar to many existing papers [21], the wind power is modelled by the multi-scenario model, which can be built via the scenario generation and reduction based on probabilistic wind power forecast.

The charge load dispatch model is modified for wind power. First, the objective function is modified to minimize the generation cost expectation in different scenarios, as shown in

$$\min F = \sum_{t=1}^{T}\sum_{gi}\left[S_{gi}u_{gi,t}(1-u_{gi,t-1}) + \sum_{s} prob_s f_{gi}(p_{gi,t,s})\right]. \tag{25}$$

Second, the dispatched wind power should be less than the simulated wind power in every scenario, i.e.,

$$0 \le RW_{wi,t,s} \le W_{wi,t,s}. \tag{26}$$

Finally, the conventional unit power is re-dispatched to balance wind power in every scenario. The operation of conventional units should meet the intra-scenario power adjustment constraints shown in

$$p_{gi,t,s_1} - p_{gi,t,s_2} \le \Delta_{gi} \tag{27}$$

as well as their constraints in every scenario. The stochastic nature of wind power is described by possible scenarios. Corrective actions of conventional units are needed to mitigate power unbalance caused by wind power volatility (real wind power changing from one scenario to another) and the correction scale is restricted by permissible adjustment range of the units.

The charge/discharge power can also be dispatched to balance wind power. However, it isn't considered in this paper to guarantee trip need of users can be met all the time, reliably and sufficiently. Replace (1), grid constraints and conventional unit constraints with (25), scenario grid constraints and scenario unit constraints, take (26) and (27) into consideration, and we can obtain the charge load dispatch model including wind power.

The proposed model is two-stage. The unit commitment and charge/discharge power of EVs are determined are on first-stage and the generation output done on the second-stage. However, by means of the dual multipliers of the second-stage problem, the problem is transformed into a series of one-stage single EV/unit problems.

B. Modification on Algorithm

Due to wind power, the problem becomes a multiscenario problem and so are the coupled constraints. The dual theory and ALR algorithm has been validated to solve multiscenario UC problem in a distributed framework [22]. Here the similar idea is adopted and the dispatch signals (dual multipliers) can be extended to the multiscenario ones. *AL* can be modified as

$$\begin{aligned} AL = F &+ \sum_{t=1}^{T}\sum_{s} prob_s \lambda_{t,s} \\ &\times \left(P_{L,t} + \sum_{ei} rpch_{ei,t} - \sum_{gi} p_{gi,t,s} - \sum_{wi} RW_{wi,t,s}\right) \\ &+ \sum_{t=1}^{T}\sum_{s} prob_s \mu d_{t,s}\left(Rd_t - \sum_{gi} pdr_{gi,t,s}\right) \\ &+ \sum_{t=1}^{T}\sum_{s} prob_s \mu u_{t,s}\left(Ru_t - \sum_{gi} pur_{gi,t,s}\right) \\ &+ \sum_{t=1}^{T}\sum_{s} prob_s^2 \left(P_{L,t} + \sum_{ei} rcph_{ei,t}\right. \\ &\left. - \sum_{gi} p_{gi,t,s} - \sum_{wi} RW_{wi,t,s}\right)^2 \end{aligned} \tag{28}$$

where both the constraints and their probability are considered. Corresponding subproblems of units, wind farms, aggregators, and EVs can be obtained. In addition, the multiplier update method is in the form of

$$\begin{aligned} \lambda_{t,s}^{k+1} = &\lambda_{t,s}^{k} + b \cdot prob_s \left(P_{L,t} + \sum_{ei} rcph_{ei,t}\right. \\ &\left. - \sum_{gi} p_{gi,t,s} - \sum_{wi} RW_{wi,t,s}\right). \end{aligned} \tag{29}$$

The consideration of wind power affects the convexity of the problem further. ALR is necessary to manage the proposed multiscenario model [22]. Thus, it is essential to introduce the EV aggregators and the layered and distributed framework to avoid ill-conditioned subproblems.

VI. Case Study

Case studies are carried out on IEEE-RTS [23]. There are 80 million cars in China, where the maximal electricity load is 500 GW. At the same ratio, the number of EVs is assumed to be 50 000 with 10% EV penetration. The EVs are divided into 50 aggregators on average. The trip pattern distribution such as the departure time and trip distance can be found in [24], [25], and the distribution of EV types is assumed as that in Table I.

TABLE I
Type Distribution of EVs

Types of EVs	Capacity	Maximal Charge Power	Percentage
1	20 kWh	3.2 kW	60%
2	30 kWh	4.8 kW	30%
3	40 kWh	6.4 kW	10%

The comparison between the proposed method (*Method 3*) and existing distributed method in [13] (*Method 2*) is included. Due to the large number of EVs, the problem appears to be intractable for the centralized method (*Method 1*). What's more, Method 2 is related to the number of EVs and will introduce ill-conditioned individual EV problems. On theory, it cannot handle the charge control of vast EVs. As a result, an *artificial group* is considered, in which the EVs attached to the same aggregator are with the identical trip and technique parameters and the aggregators can be seen as enlarged EVs. The charge of aggregators is optimized instead and the obtained charge/discharge power of aggregators are divided to EVs on average since the EVs are identical. If the aggregator could meet the enlarged constraints, every EV would meet its own constraints. Thanks to the limited number of aggregators, Method 1 and Method 2 works well with the artificial EV group considered. Thus the comparison is carried out to explain the advantage of Method 3 on reducing generation cost and the results of the Method 1 are chosen as reference.

On the other hand, the simulation on Method 3 is carried out to test its performance in a more real case. A *simulated group* is considered, in which the parameters of different EVs in the same aggregator are diverse.

EV parameters are sampled by the Monte Carlo Method according to the related distributions. There are 50 kinds of parameters for the artificial group while for the simulated group the number is 50 000.

The case studies are presented in two parts. In Section VI-A, the comparison between the existing and proposed methods is emphasized while the framework is extended to include multiscenario wind power in Section VI-B.

A. Cases Without Wind Power

In this part, the 300 MW hydro generation is omitted and the maximal conventional load is modified to be 2550 MW correspondingly, which is 2850 MW in the standard IEEE-RTS.

The generation cost of the methods is compared in Table II with the artificial group considered. The Method 1 carries out a unified optimization on the whole controllable resources and obtains the lowest generation cost. The generation cost gotten by Method 2 and Method 3 is a little higher. However, Method 1 is not able to dispose of large population of EVs and the user privacy is influenced.

Compared with Method 2, Method 3 can obtain less generation cost in both pure charge control and V2G, considering the unit operation and optimizing the generation cost directly. There are some intra-temporal constraints on generation units, which results in that the generation cost is not only related to

TABLE II
GENERATION COST OF DIFFERENT METHODS (WITHOUT WIND POWER)

Modes	Cost	Centralized	Existing Distributed	Proposed Method
Pure Charge Control	Fuel	723 621.21	723 837.29	723 143.86
	Start/Shut	1 780	2 200	2 300
	Sum	725 401.21	726 057.29	725 443.86
V2G Control	Fuel	721 706.736	723 408.50	722 251.96
	Start/Shut	2 020	2 020	1 780
	Sum	723 726.73	725 428.50	724 031.96

TABLE III
PRODUCTION INDEXES IN DIFFERENT CASES (WITHOUT WIND POWER)

Indexes	Fast Charge	Pure Charge Control	V2G Control
Fuel cost($)	733 884.79	723 902.75	722 136.11
Startup/Shutdown cost($)	2 080	1 780	1 700
Total cost($)	735 964.79	725 682.75	723836.11
Thermal unit cost($/MWh)	13.99	13.79	13.75

fuel cost in all timeslots but also influenced by the start-up/shut-down cost and adjustment between/among continuous timeslots. Method 2 is efficient in optimizing the former (fuel cost) but it neglects the latter. When intra-temporal constraints (e.g., the start-up/shut down cost, minimal on/off time and ramp rate) are overlooked, the generation cost obtained by Method 2 is \$677 937.8 while for Method 3 it is \$677 938.1. On the other hand, if there were enough EVs, the load curve was flattened to be straight and Method 2 could do as well as Method 3 in minimizing the generation cost.

The applicability of Method 3 for masses of EVs is analyzed and tested in a more real case with the simulated group considered. The simulated charge energy demand is 957.63 MWh, covering 1.6% of whole electricity demand. The uncoordinated fast charge (Case I), pure charge control (Case II), and V2G control (Case III) are analyzed. In Case II and III, Method 3 is adopted. The generation cost and net load curves are shown in Table III and Fig. 3, respectively. The generation cost is reduced in Case II and Case III. Pure charge control and V2G are able to level the load curve, decrease the start-up/shut-down cost and improve the operating efficiency of units.

The iteration process is presented in Fig. 4. As shown, no matter whether the pure charge control or the V2G control is considered, there are always some oscillations in the distributed framework. In contrast to it, the gap decreases monotonously in the layered and distributed framework. The introduction of the EV aggregators help to avoid the oscillations and accelerate the convergent process, which is both important and necessary.

Based on the studies in this part, it is safe and easy to reach the conclusions that: 1) the layered and distributed framework can provide a near optimal charge control scheme and performs better than the existing distributed methods and 2) it applies to vast EVs and is proper for both pure charge control and V2G control.

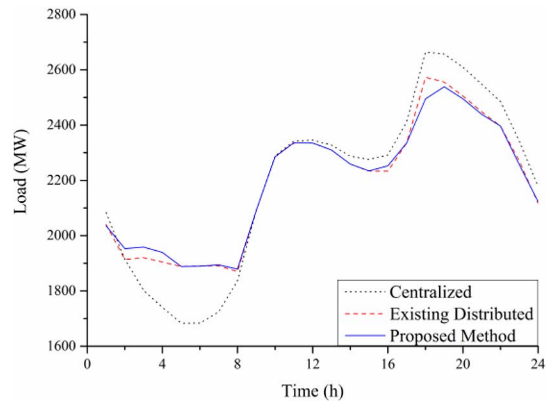

Fig. 3. Load curves in different cases (without wind power).

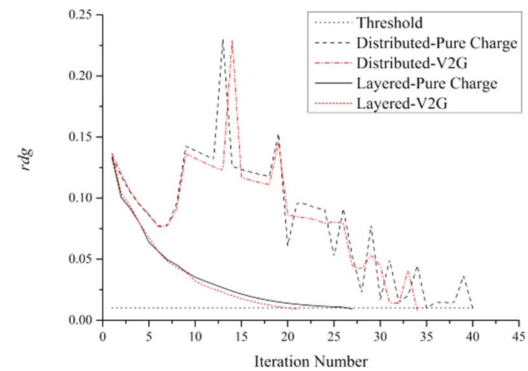

Fig. 4. Iterative process of pure charge/V2G control in different framework.

B. Cases Considering Wind Power

The 300-MW hydro generation is replaced by 960-MW wind power in this part. The distribution of forecasted wind power is assumed to be normal, whose standard deviation is assumed to be 20% of the expectation. The power statistics of a certain wind farm in the Northwest China Grid are chosen as the wind power expectation and the wind power is enlarged at the same ratio as wind generation capacity.

When the artificial EV group is considered, the generation cost obtained by different methods is shown in Table IV. Like those in Section VI-A, the similar conclusions can be obtained. In Method 2, EVs are coordinated to balance wind power. The cooperation among EVs is included but the cooperation between EVs and generation, especially wind power is not considered. For example, there may be wind spillage in some extreme wind power scenarios for the safe and economic grid operation. EVs can track the original wind power curve but they fail to track the curve considering wind spillage via Method 2. The optimal operation of conventional generators and wind farms are included in Method 3 which takes the cooperation between EVs and generation into account and achieves less generation cost.

For the simulated EV group, the generation cost and net load curves of different cases are shown in Table V and Fig. 5. Method 3 still works and the generation cost is reduced in Case II and Case III, too. V2G is more flexible and can provide more controllable resources for the grid than the pure charge control. Although the wind spillage in Case III is a little larger than that in Case II, V2G helps to keep conventional units operating

TABLE IV
GENERATION COST OF DIFFERENT METHODS (INCLUDING WIND POWER)

Modes	Cost	Centralized	Existing Distributed	Proposed Method
Pure Charge Control	Fuel	615647.26	616 625.53	616 373.55
	Start/Shut	1 940	1 940	2 060
	Sum	617 587.26	618 565.53	618 393.55
V2G Control	Fuel	609 215.04	612 530.043	609 721.62
	Start/Shut	1 700	1 900	1 860
	Sum	610 915.04	614 430.043	611 581.62

TABLE V
PRODUCTION INDEXES IN DIFFERENT CASES (INCLUDING WIND POWER)

Indexes	Fast Charge	Pure Charge Control	V2G Control
Fuel cost($)	629 835.28	615 606.48	611 051.57
Startup/Shutdown cost($)	1 980	1 900	1 860
Total cost($)	631 815.28	617 506.48	612 911.57
Wind Spillage (MWh)	146.38	33.00	50.08
Thermal unit cost($/MWh)	13.72	13.45	13.33

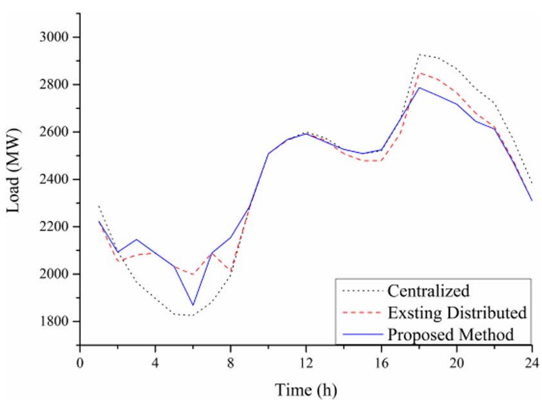

Fig. 5. Net load curves in different cases (including wind power).

more efficiently. The cost for per unit energy is less and the total generation cost is reduced. Charge control and V2G can not only reduce fluctuations of load but also improve operating efficiency of conventional units.

In this part, the proposed framework is verified still valid when the multi-scenario wind power is taken into consideration and able to coordinate EVs and stochastic wind power.

VII. CONCLUSION

We have proposed a novel layered and distributed framework to dispatch charge load of considerable EVs to minimize the generation cost, with stochastic wind power considered. The framework features in EV aggregators which play an important part in coordinating different layers. The necessity and function of aggregators is explained according to APP, while LR provides the decomposition and cooperation theory and modified ALR is proposed to dispose of large populations of EVs. The feasibility and validity of the proposed framework is verified via case studies on IEEE-RTS1979. Compared with the existing methods, the proposed method gains the following advantages: 1) it applies to a large number of EVs and can achieve less generation cost directly; 2) not only is the cooperation between EVs considered, the synergy between EVs and generation especially the stochastic wind power is also included; and 3) the method is with a larger application scope including the problems with coupled constraints.

The proposed framework also throws some light on the dispatch of other kinds of controllable load and implies a novel market mechanism considering the interaction between generation and load. However, the power flow constraints and auxiliary services provided by EVs are not included, which need further studies.

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