

Distributed Optimization-Based Hourly Coordination for V2G and G2V

Farnaz Safdarian, Logan Lamonte, Amin Kargarian, Mehdi Farasat
Division of Electrical and Computer Engineering
Louisiana State University
Baton Rouge, USA
fsafda1@lsu.edu

Abstract—Network-constrained economic dispatch (NCED) problem, which takes into account the random mobility of electric vehicles (EV) and additional variables corresponding to each EV's charge/discharge cycles, is large scale, complex and computationally expensive. To reduce the computational burden associated with this optimization problem, distributed optimization is introduced. Since EVs randomly move from one bus to another bus, this paper proposes a temporal, rather than a geographical, decomposition approach to divide a ramp-constrained NCED. Thousands of EVs are considered over the scheduling horizon in order to take advantage of parallel computing and achieve reduced solution time. A ramp-constrained NCED is formulated for each sub-horizon while the connections between subproblems are modeled as shared variables/constraints. In order to coordinate the subproblems and find the optimal solution for the entire operation horizon, distributed auxiliary problem principle (APP) is proposed. Further, an efficient initialization strategy is presented to enhance the convergence time of the solution algorithm. The proposed method is employed to solve a week-ahead NCED on a 6-bus and IEEE 118-bus test systems. The results are compared with those of a centralized approach and effectiveness of the proposed method in reducing the solution time is verified.

Keywords—Time decomposition, distributed optimization, overlapping time intervals, security-constrained economic dispatch, accelerated auxiliary problem principle, electrical vehicles, batteries, energy management.

I. INTRODUCTION

The ever increasing popularity of plug-in electric and fully electric vehicles (EV) is creating new challenges for power system operation and planning. The unique economic and environmental incentives from EV use is driving deep market penetration while leaving a gap in economic dispatch modeling capabilities. [1] The future of EVs extends past being a load on the system; vehicle-to-grid (V2G) integration enables bi-directional power flow, allowing the vehicle to either absorb/inject power from/into the grid. Bi-directional power flow, when coupled with other complicating factors, such as random charging behavior, usage patterns, energy requirements, topological grid interconnections, create a multiplex based situation. Limited by various operation constraints, nonlinearities, and uncertainties, several optimization goals must be pursued. EVs can be represented as “movable” energy storage units; however, due to the individual behavior of each EV, this requires representing each EV with a unique variable. In power systems with thousands or even millions of EVs, the

total number of variables and constraints increase in lockstep with system size, consequently increasing computational burdens. Solving large optimization problems with a centralized method within an acceptable time period quickly becomes problematic [2], [3].

Several studies focus on energy management of networks which include EVs. Possible impacts of widespread hybrid electrical vehicles (HEVs) on the grid is investigated in [4]. In [5], an energy management strategy for vehicles with a fuel cell power source and two energy storage devices, i.e., batteries and ultracapacitors, is introduced. A hybrid artificial intelligence technique is presented in [6] to solve a complex energy management problem with a large number of resources, including EVs connected to the electric network. In [7], methods to store power at the most efficient times of the driving cycle are discussed. Various control and optimization issues for both charging and scheduling of HEV's in a bidirectional V2G network are surveyed in [8]. Unit commitment in a V2G infrastructure, while considering operating expenses and environmental impact is studied in [9]. In [2], centralized control of HEV charging cycles to reduce grid demand and costs, and increase efficiency of the overall network is demonstrated. A short-term unit commitment problem is introduced in [10] with the utilization of grid-tied EVs and considering Gridable Vehicles (GVs) of V2G. Energy scheduling is addressed in [11] by using different resources and emphasizing distributed generation coupled with V2G. A methodology is presented in [12] to solve the energy management problem with high penetration of distributed generation and EVs with gridable capability. Joint scheduling of HEVs and renewable energy sources through economic dispatch is examined in [13] via dispatching mode, modeling, and algorithms. In [14], it is shown that the economic dispatch control of grid-connected HEVs can possibly result in lower energy costs via fuel shifting and fuel discharging. In [15], a method is proposed for a day-ahead stochastic security-constrained unit commitment problem in the presence of wind power generation and EVs. In [16], coordinated integration of aggregated plug-in electric vehicle (PEV) fleets and renewable energy sources (wind energy) is studied. Stochastic security-constrained unit commitment (Stochastic SCUC) model, which minimizes the expected grid operation cost while considering the random behavior of PEVs is employed.

Several methods are introduced to reduce computational burden of energy management and scheduling problems

through distributed optimization algorithms, which take advantage of parallel computing. Geographical decomposition approaches have been presented in the literature [17-19], to solve large operation and planning problems for power systems. However, since EVs are randomly moving from one bus to another, the problem cannot easily be decomposed over geographical areas.

This paper proposes a temporal decomposition approach to divide a network-constrained economic dispatch (NCED). Thousands of EVs are considered over the scheduling horizon in order to take advantage of parallel computing and achieve reduced solution time. Since the sub-problems are not isolated, the consistency constraints between subproblems, such as ramping limitations, must be modeled. To this end, a ramp-constrained NCED is formulated for each sub-horizon while the connections between subproblems are modeled as shared variables/constraints. In order to coordinate the subproblems and find the optimal solution for the entire operation horizon, distributed auxiliary problem principle (APP) is proposed. Further, an efficient initialization strategy is presented to enhance the convergence time of the solution algorithm. The proposed method is applied to solve a week-ahead NCED on a 6-bus and IEEE 118-bus test systems and promising results are obtained.

II. PROBLEM DESCRIPTION

A. Economic Dispatching including Electrical Vehicles

The goal is to determine the hourly ramp-constrained NCED along with the dispatch of generating units, while considering the charge/discharge states of EV fleets. The objective function given in (1) is to minimize cost. This includes generation cost, operational costs of EV fleets for the base case, and availability cost for providing spinning reserve for each scenario, plus the expected cost of corrective actions in scenarios to compensate for uncertainties. The proposed formulation is a stochastic optimization problem with load forecast errors, power system component outages, number of EVs in a fleet, and their energy requirements considered as variables.

The Monte Carlo simulation method is utilized in the proposed stochastic model. Random outages in power systems are represented by incorporating probability distribution functions and forced outage rates. Load forecast errors, EV energy consumption patterns, and the number of EVs in a fleet are represented by truncated normal distribution functions. [16] The mean values are the forecasts, and the standard deviations are percentages of the mean values. Forward and backward algorithms are developed to reduce the number of scenarios with an acceptable accuracy [20]. The convex operation cost of aggregated EVs depends on the number of vehicles and charging/discharging cycles [21].

$$\begin{aligned} \min & \left[\sum_t \sum_u (p^b \times f(p_{ut})) + \sum_t \sum_v p^b \cdot C_{v,t} \right] \\ & + \sum_s p^s \left[\sum_t \sum_u f(P_{ut}^s) + \sum_t \sum_v C_{v,t}^s \right] \\ & + \left[\sum_t \sum_u (f^a(\Delta_{u,t}^{max})) \right] \end{aligned} \quad (1)$$

$$f(p_{ut}) = a_u \cdot p_{ut}^2 + b_u \cdot p_{ut} + c_u \quad (2)$$

where a_u , b_u , and c_u are cost coefficients for generating unit u , t refers to time interval, u refers to generating units, f is the generation cost function, p_{ut} is power generated by unit u at time t , p^b defines the probability of the base case solution. $\Delta_{u,t}^{max}$ maximum permissible power adjustment of a unit, $C_{v,t}$ represents operational cost of EV fleet.

s. t.

Constraints for the base case:

$$\begin{aligned} \sum_u P_{ut} + \sum_v P_{v,t} - \sum_d P_{d,t}^d \\ = \sum_{i=1, i \neq j}^N \frac{\delta_{it} - \delta_{jt}}{X_{ij}} \quad \forall u, t, v, i, j \end{aligned} \quad (3)$$

$$p_{ijt} = \frac{\delta_{it} - \delta_{jt}}{X_{ij}} \quad \forall ij, \forall t \quad (4)$$

$$\delta_{ref,t} = 0 \quad \forall t \quad (5)$$

$$\underline{P}_u \leq p_{ut} \leq \overline{P}_u \quad \forall u, \forall t \quad (6)$$

$$p_{ut} - p_{u(t-1)} \leq UR_u \quad \forall u, \forall t \quad (7)$$

$$p_{u(t-1)} - p_{ut} \leq DR_u \quad \forall u, \forall t \quad (8)$$

$$\underline{P}_{ij} \leq p_{ijt} \leq \overline{P}_{ij} \quad \forall ij, \forall t \quad (9)$$

$$\underline{\delta}_i \leq \delta_{it} \leq \overline{\delta}_i \quad \forall i, \forall t \quad (10)$$

$$E_{v,t}^{net} = P_{dc,v,t} - \eta_v \cdot P_{c,v,t} \quad (11)$$

$$P_{v,t} = P_{dc,v,t} - P_{c,v,t} \quad (12)$$

$$I_{dc,v,t} + I_{c,v,t} + I_{i,v,t} = N_{v,t} \quad (13)$$

$$I_{c,v,t} \cdot P_{c,v}^{min} \leq P_{c,v,t} \leq I_{c,v,t} \cdot P_{c,v}^{max} \quad (14)$$

$$I_{dc,v,t} \cdot P_{dc,v}^{min} \leq P_{dc,v,t} \leq I_{dc,v,t} \cdot P_{dc,v}^{max} \quad (15)$$

$$E_{v,t} = E_{v,t-1} - E_{v,t}^{net} - (1 - N_{v,t}) \cdot DR_{v,t} \quad (16)$$

$$E_v^{min} \leq E_{v,t} \leq E_v^{max} \quad (17)$$

$$E_{v,0} = E_{v,NT} \quad (18)$$

$$C_{v,t} = N_{v,t} \cdot (a \cdot p_{v,t}^2 + b \cdot P_{v,t} + c) \quad (19)$$

where i and j are indices for buses, ij is the index for lines, p_{ij} denotes power flow in line ij , δ_i is the voltage angle of bus i , X_{ij} is the reactance of line ij , $\overline{P}_u$ and $\underline{P}_u$ refer to the maximum and minimum limits of generating unit u , $\overline{P}_{ij}$ and $\underline{P}_{ij}$ refer to the maximum and minimum limits of line ij , UR_u and DR_u show the ramping up and ramping down limits of unit u , $E_{v,t}^{net}$ is the Net discharged energy of EV fleet at time t , $P_{dc,v,t}$ and $P_{c,v,t}$ represent discharge/charge power of EV fleet, η_v is the cycle charging efficiency of PEV fleet, $I_{dc,v,t}$, $I_{c,v,t}$, $I_{i,v,t}$ represent discharge/charge and idle mode of EV fleets, $N_{v,t}$ Status of grid connection of fleet at time t , E_v^{min} , E_v^{max} min/max energy stored in batteries of EV fleet v , and $E_{v,0}$ and $E_{v,NT}$ refer to the initial and terminal stored energy in EV fleet v .

The base constraints (3)-(20) are deterministic and include NCED constraints (3)-(10) and EV constraints (11)-(20). The EV constraints include the hourly injected/consumed energy and power to/from the network by EVs (11)-(12). The hourly charge/discharge/idle modes of fleets are presented in (13). Charge/discharge power limitations are presented in (14)-(15). The hourly energy balance of EV batteries is considered in (16). The energy limitation of each fleet is given in (17)-(18). The charge/discharge cost curve of EV batteries is provided in (19). This represents the depth of discharge and cycles to failure of the battery required for calculating the cost of charged/discharged energy to/from EV batteries. In the consumer-controlled scheme, the aggregated state of charge (SOC) of EVs is set to be fixed at specific operation periods (11). It is assumed that the SOC is at 100% when an EV fleet is leaving the station [16].

Constraints for each scenario:

$$\sum_u P_{ut}^s + \sum_v P_{vt}^s - \sum_d P_{dt}^{d,s} = \sum_{i=1, i \neq j}^N \frac{\delta_{it}^s - \delta_{jt}^s}{X_{ij}} \quad \forall u, t, v, i, j, s \quad (20)$$

$$p_{ijt}^s = \frac{\delta_{it}^s - \delta_{jt}^s}{X_{ij}} \quad \forall ij, \forall t, \forall s \quad (21)$$

$$\delta_{ref,t}^s = 0 \quad \forall t \quad (22)$$

$$\underline{P}_u \leq p_{ut}^s \leq \overline{P}_u \quad \forall u, \forall t \quad (23)$$

$$\underline{P}_{ij} \leq p_{ijt}^s \leq \overline{P}_{ij} \quad \forall ij, \forall t \quad (24)$$

$$\underline{\delta}_i \leq \delta_{it}^s \leq \overline{\delta}_i \quad \forall i, \forall t \quad (25)$$

$$E_{v,t}^{net,s} = P_{dc,v,t}^s - \eta_v \cdot P_{c,v,t}^s \quad (26)$$

$$P_{v,t}^s = P_{dc,v,t}^s - P_{c,v,t}^s \quad (27)$$

$$I_{dc,v,t}^s + I_{c,v,t}^s + I_{i,v,t}^s = N_{v,t} \quad (28)$$

$$N_{v,t} \cdot I_{c,v,t}^s P_{c,v}^{min} \cdot NE_v^s \leq P_{c,v,t}^s \leq N_{v,t} \cdot I_{c,v,t}^s P_{c,v}^{max} \cdot NE_v^s \quad (29)$$

$$N_{v,t} \cdot I_{dc,v,t}^s P_{dc,v}^{min} \cdot NE_v^s \leq P_{dc,v,t}^s \leq N_{v,t} \cdot I_{dc,v,t}^s P_{dc,v}^{max} \cdot NE_v^s \quad (30)$$

$$E_{v,t}^s = E_{v,t-1}^s - E_{v,t}^{net,s} - (1 - N_{v,t}) \cdot DR_{v,t}^s \cdot NE_v^s \quad (31)$$

$$E_v^{min} \cdot NE_v^s \leq E_{v,t}^s \leq E_v^{max} \cdot NE_v^s \quad (32)$$

$$E_{v,0}^s = E_{v,NT}^s = E_{v0} \cdot NE_v^s \quad (33)$$

$$C_{v,t}^s = N_{v,t} \cdot (a \cdot P_{v,t}^{s,2} + b \cdot P_{v,t}^s + c) \quad (34)$$

$$-\Delta_{u,t}^{max} \leq P_{u,t}^s - P_{u,t} \leq \Delta_{u,t}^{max} \quad (36)$$

$$P_u^{min} \cdot I_{u,t} \leq P_{u,t}^s \leq P_u^{max} \cdot I_{u,t} \quad (37)$$

The EV fleet scenario constraints are given in (20)–(37). Equations (20)–(25) represent NCED constraints for each Monte Carlo scenario. The parameter NE_v^s is an uncertain

input that shows the ratio of the number of EVs in the scenario to the number of base case EVs. The scenario corrective action is enforced by (36)–(37) where the hourly cost of corrective action $f^a(\Delta_{u,t}^{max})$, is included in objective function (1).

Considering the grid complexity along with the stochastic nature and mobility of EVs, the optimization problem in (1)–(37) is large scale and nondeterministic. The solution to this problem (without decomposition) demands high computational capabilities. It is proposed in [16] to decompose such problems into a master mixed-integer programming (MIP) problem with several linear programming (LP) subproblems and use Benders cuts for scenario reduction. In this work, in order to further alleviate the computational burden and reduce the solution time, time decomposition is applied following Benders decomposition.

B. Time Decomposition

Solution time is affected by the number of variables and constraints. In order to speed up the solution algorithm of NCED, a time decomposition approach is proposed based on the authors' previous work [3]. With this approach, the problem is divided into smaller sub-horizons, where each represents a subproblem that includes a subset of variables and constraints. Solving sub-horizons independently can result in two different values at the point in-between individual events. This calls for instant change of generating units outputs; however, this is not possible due to ramping limitations. Therefore, intervals must be able to coordinate with each other. An extra time interval of one hour is added at the end of each sub-horizon and treated as a shared variable that must be equal for neighboring problems. The main goal is time reduction by reducing the computational load through parallel computing. The distributed coordination algorithm allows parallel computing while reaching an optimal solution for the entire scheduled time horizon.

III. COORDINATION ALGORITHM

Utilizing auxiliary problem principle [22], which is a parallel based coordination strategy, the sub-horizons can be coordinated and suboptimal or infeasible results avoided. An iterative coordination algorithm is presented that provides a parallel solution for the NCED subproblems. Relaxing the consistency constraints in the objective function of each sub-horizon is possible through the concept of augmented Lagrangian relaxation.

A. Auxiliary Problem Principle

The proposed coordination algorithm is based on the auxiliary problem principle (APP). With roots in Lagrangian relaxation, APP is iterative and can find an optimal solution for coupled subproblems [22]. Special features allow for sequences of auxiliary problems to coordinate subproblems, creating a practical approach for parallel optimization through the approximation of shared variables for each iteration while being based on the iteration prior.

Considering a one-week scheduling horizon that can be decomposed into NS subproblems, assume two consecutive subproblems, referred to as subproblems n and $n+1$. The

output power of generating units in the final time interval of n and the first time interval of $n+1$ must match. To meet this requirement, an overlapping time interval, tc , is added to subproblem n . Time interval tc is shared between neighboring subproblems. For each generating unit, the optimal output power in overlapping time interval tc must be equal to the generated power in time interval 1 of subproblem $n+1$. Denoting the shared variables of subproblems n and $n+1$ by ϕ_n and ϕ_{n+1} , respectively, and remembering that ϕ_n and ϕ_{n+1} are essentially the same, the following consistency constraint must be satisfied for all the generating units

$$\phi_n - \phi_{n+1} = 0 \quad (38)$$

The constraint in (38) is a hard constraint, which potentially can result in the sub-optimality of the solution. This is not desirable. Thus, using the concept of augmented Lagrangian relaxation, this hard constraint is relaxed by adding a penalty function to the objective function (1). This can be seen in the formulation (1-10) of subproblem n at iteration k , as follows

$$\begin{aligned} \min_{(x_n^k, \phi_n^k)} \sum_{u,t} f(p_{u,t}^k) \quad (39) \\ + \left(\frac{\rho}{2} \left\| \Phi_n^k - \Phi_n^{*k-1} \right\|^2 + \gamma \Phi_n^{k\top} \left(\Phi_n^{*k-1} - \Phi_{n+1}^{*k-1} \right) \right. \\ \left. + \lambda^{(k-1)\top} \Phi_n^k \right) \\ \text{s.t.} \\ h_n(x_n^k, \Phi_n^k) = 0 \\ g_n(x_n^k, \Phi_n^k) \leq 0 \\ x_n^k = \{p_{u,t,n}^k, P_{v,t}, I_{dc,v,t}, I_{c,v,t}, I_{i,v,t}\}, \\ \Phi_n^k = \{p_{u,tc,n}^k\}, \Phi_{n+1}^{*k-1} = \{p_{u,tc,n+1}^{*k-1}\} \end{aligned}$$

Here, $\top$ is a transpose operator, x_n is the set of output power of generating units during sub-horizon n , ϕ_n is the set of output power of generating units in the overlapping time interval tc , λ^k is the vector of Lagrange multipliers at iteration k , ρ and γ are suitable positive constants. Φ_n^{*k-1} and Φ_{n+1}^{*k-1} indicate the values of the shared variables of subproblems n and $n+1$ that are determined at iteration $k-1$, and Φ_n^k is the shared variable of subproblem n that needs to be determined in iteration k . In fact, Φ_n^{*k-1} and Φ_{n+1}^{*k-1} in (39) are known values while Φ_n^k is a decision variable.

A similar ramp-constrained NCED is formulated for subproblem $n+1$ in the following

$$\begin{aligned} \min_{x_{n+1}^k, \Phi_{n+1}^k} \sum_{u,t} f(p_{u,t}^k) \quad (40) \\ + \left(\frac{\rho}{2} \left\| \Phi_{n+1}^k - \Phi_{n+1}^{*k-1} \right\|^2 + \gamma \Phi_{n+1}^{k\top} \left(\Phi_{n+1}^{*k-1} - \Phi_n^{*k-1} \right) \right. \\ \left. - \lambda^{(k-1)\top} \Phi_{n+1}^k \right) \\ \text{s.t.} \\ h_{n+1}(x_{n+1}^k, \Phi_{n+1}^k) = 0 \\ g_{n+1}(x_{n+1}^k, \Phi_{n+1}^k) \leq 0 \end{aligned}$$

$$\begin{aligned} x_{n+1}^k &= \{p_{u,t,n}^k, P_{v,t}, I_{dc,v,t}, I_{c,v,t}, I_{i,v,t}\}, \\ \Phi_{n+1}^k &= \{p_{u,tc,n+1}^k\}, \Phi_n^{*k-1} = \{p_{u,tc,n}^{*k-1}\} \end{aligned}$$

where Φ_n^{*k-1} and Φ_{n+1}^{*k-1} are known values while Φ_{n+1}^k is a decision variable. The NCED subproblems are solved iteratively. The penalty multiplier λ needs to be updated at the end of each iteration as follows

$$\lambda^k = \lambda^{k-1} + \alpha \left(\Phi_{n+1}^{*k} - \Phi_n^{*k} \right) \quad (41)$$

where α is a suitable positive constant. Note that the value of the Lagrange multiplier λ in each iteration corresponds to the cost of maintaining the consistency constraint.

B. Initialization

The performance of distributed/decentralized optimization algorithms is heavily reliant on initial conditions. Convergence performance, or the number of iterations and the optimality gap, can vary based on initial conditions. Ideal initial conditions result in convergence of the proposed APP-based distributed NCED in fewer iterations compared to scenarios. Initial conditions are both problem and system dependent and research to set proper initial conditions is currently ongoing within the power systems and operations community.

Computational time is the main focus of the proposed time decomposition framework. Thus, selection of a good starting point is imperative. Power system characteristics allow to propose a method for ideal shared variable initiation. Initializing variables start by ignoring the overlapping time intervals and shared variables, (to make the sub-horizons become independent), and then solving the NCED subproblems in parallel. Ignoring the ramping rates of the generators by removing the shared variables does not result in a large solution error. This is due to the demand characteristics in power systems. Although the results of isolated subproblems may not be feasible, they are of high potential for proper initial states.

IV. CASE STUDY

The proposed algorithm is employed to solve a week-ahead NCED problem on a 6-bus and the IEEE 118-bus systems. EVs in various locations are categorized into fleets based on driving characteristics. The available energy, maximum/minimum capacity, and charge/discharge power of individual vehicles are aggregated in EV fleet characteristics, representing maximum/minimum capacities, SOC, and maximum/minimum charging/discharging capabilities.

EV fleet characteristics include starting locations and destinations of EV fleets, departure and arrival times at designated locations, and EV charging locations and patterns which could be bundled into power system operations. A random number of EVs is assumed for each fleet. SOC, energy consumption, and maximum/minimum capacity of an EV fleet are a function of the number of EVs and their operating characteristics. SOC is the ratio of available energy to maximum storable energy in the battery. [23] The energy consumption in a fleet depends on the number of EVs and their energy requirements. The driving habits of a fleet would determine the charging/discharging patterns of the aggregated EVs [16]. Tables I lists the five

fleets that are the results of benders decomposition in [16]. The charging efficiency of a fleet is 85% which is the ratio of energy stored in the battery to the energy drawn from the grid.

TABLE I

EV FLEET TRAVEL CHARACTERISTICS [16]									
PEV Fleet No.	Number of PEVs	First Trip				Second Trip			
		Departure		Arrival		Departure		Arrival	
		Time	Bus	Time	Bus	Time	Bus	Time	Bus
1	3400	6:00	5	8:00	1	17:00	1	19:00	5
2	2000	7:00	4	8:00	2	16:00	2	17:00	4
3	1000	5:00	4	7:00	2	16:00	2	18:00	4
4	1600	5:00	6	6:00	3	17:00	3	18:00	6
5	2000	7:00	5	9:00	3	18:00	3	20:00	5

The operation horizon is divided into seven equal sub-horizons, each including 24 intervals. To have a fair comparison, $\beta, \rho, \gamma = 0.2$ and $\lambda = 1$ in all cases. Consistency constraints are modeled as shared variables to form the connections between subproblems in order to optimize the system over the entire time span. In this way, the overall optimal cost for the entire system is achieved. To evaluate the performance of the proposed distributed NCED algorithm, a convergence index is used to measure the relative difference between the total costs determined by the distributed NCED (f^d) and the centralized NCED (f^*), which is considered as the benchmark.

$$rel = \frac{|f^* - f^d|}{f^*} \quad (42)$$

The closer the convergence measure gets to zero, a more precise solution is obtained. All simulations are carried out in MATLAB using YALMIP [24] as a modeling software and Gurobi solver on a 3.7 GHz personal computer with 16GB of RAM, virtually modelling parallel computing.

A. 6-Bus System

EVs in various locations are categorized into different fleets based on their driving characteristics. The available energy, maximum/minimum capacity and charge/discharge power of individual vehicles are aggregated into EV fleet characteristics representing maximum/minimum capacities, SOC, and maximum/minimum charging/discharging capabilities. Table II shows characteristics of the five fleets in the 6-bus system.

TABLE II

EV FLEET CHARACTERISTICS FOR 6-BUS [16]							
PEV Fleet No.	Min Cap. (MWh)	Max Cap. (MWh)	Min Charge /Discharge (kW)	Max Charge /Discharge (MW)	a (\$/MW ²)	b (\$/MW)	c (\$/h)
1	13.152	65.76	7.3/6.2	24.8/21.08	0.17	8.21	0
2	10.96	54.8	7.3/6.2	14.58/12.4	0.20	8.21	0
3	5.48	27.4	7.3/6.2	7.29/6.2	0.41	8.21	0
4	8.768	43.84	7.3/6.2	11.67/9.92	0.25	8.21	0
5	10.96	54.8	7.3/6.2	14.58/12.4	0.20	8.21	0

The topology of the 6-bus system is shown in Fig. 1 and tables III-V summarize data of this system.

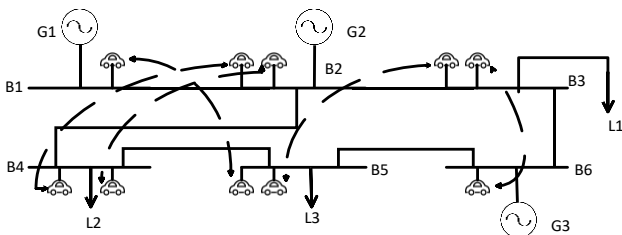


Fig. 1. Six-bus test system.

TABLE III

GENERATOR DATA FOR 6-BUS SYSTEM

Unit	Pmin (MW)	Pmax (MW)	a (MBtu)	b (MBtu/MWh)	c (MBtu/MW ² h)
1	40	220	100	7	0.03
2	10	100	104	10	0.07
3	0	25	110	8	0.05

TABLE IV

NETWORK INFORMATION FOR 6-BUS SYSTEM

From Bus	To Bus	X(pu)	Flow Limit (MW)
1	2	0.170	200
1	4	0.258	200
2	3	0.037	190
2	4	0.197	200
3	6	0.018	180
4	5	0.037	190
5	6	0.140	180

TABLE V

HOURLY LOAD OVER A SAMPLE DAY HORIZON FOR 6-BUS SYSTEM

Hour	P _d (MW)	Hour	P _d (MW)	Hour	P _d (MW)	Hour	P _d (MW)
1	175	7	173	13	242	19	246
2	169	8	174	14	24	20	237
3	165	9	185	15	249	21	237
4	155	10	202	16	256	22	233
5	155	11	228	17	256	23	210
6	165	12	236	18	247	24	210

Table VI shows the convergence time, number of iterations, and rel for the 6-bus system. The operation cost using both centralized and distributed methods is \$486,900. The proposed distributed NCED converges to feasible and optimal results after one iteration plus the initialization. The computation time is 0.14 seconds which is a little less than that of the centralized method, 0.18 seconds. The rel index is almost zero upon the algorithm convergence. The distributed NCED is 22% faster than the centralized NCED.

TABLE VI

RESULTS OF 6-BUS SYSTEM

Algorithm	Iteration	rel	Time (s)
Centralized	-	-	0.18
Distributed	1+1	1e-12	0.14

B. IEEE 118-Bus System

The proposed algorithm is employed to solve NCED of a larger system, i.e. IEEE 118-bus system. Table VII shows the fleet characteristics for this system. The fleet travel schedules are similar to those in the previous case study. EV fleet travel characteristics is the same as Table I.

TABLE VII

EV FLEET CHARACTERISTICS FOR IEEE 118-BUS SYSTEM [16]

PEV Fleet No.	Min Cap. (MWh)	Max Cap. (MWh)	Min Charge /Discharge (kW)	Max Charge /Discharge (MW)	a (\$/MW ²)	b (\$/MW)	c (\$/h)
1	131.52	986.4	7.3/6.2	24.8/21.08	0.57	27.35	0
2	109.6	822	7.3/6.2	14.58/12.4	0.68	27.35	0
3	54.8	411	7.3/6.2	7.29/6.2	1.36	27.35	0
4	87.68	657.6	7.3/6.2	11.67/9.92	0.85	27.35	0
5	109.6	822	7.3/6.2	14.58/12.4	0.68	27.35	0

The operation cost using both centralized and distributed NCED algorithms is \$11,083,000. Table VIII summarizes the simulation results for the IEEE 118-bus system.

TABLE VIII

RESULTS OF IEEE 118-BUS SYSTEM

Algorithm	Iteration	rel	Time (s)
Centralized	-	-	3.08
Distributed	3+1	1e-08	1.37

Since a relative error of $1e-8$ does not have any impact on the cost, the convergence measure *rel* is considered almost zero upon convergence. The centralized NCED takes around 3 seconds, but the distributed algorithm converges after 1.3 seconds. This is approximately 55% faster compared with the centralized algorithm.

V. CONCLUSION

The impact of integrating EV fleets into power systems is evaluated. A stochastic model, which incorporates EV fleets models along with the associated constraints and requirements, is proposed. A time decomposition algorithm is devised to divide a ramp-constrained NCED problem over the scheduling time horizon. NCED subproblems are formulated, with each sub-horizon taking into account thousands of EVs connected to the network. Interdependencies between the consecutive sub-horizons, which originate from intertemporal constraints of generating units, are modeled by introducing the concept of overlapping time intervals. APP is proposed to coordinate the NCED subproblems. An initialization strategy is proposed to enhance the convergence speed of the solution algorithm. The simulation results suggest that as the size of the problem (that depends on the size of the system and the number of EVs) increases, the proposed distributed algorithm outperforms the conventional centralized NCED in terms of computational time.

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