# Optimal demand Side Management for the Sparse Scheduling of Smart Charge of EVs

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***Abstract*—In this article, we provide a proof of concept realization of the proposed demand response scheme described in [1], modelling an EV-aggregator offering smart charging[1] coordination services to several Electric Vehicles (EV). The aggregator model promotes a distributed smart charge coordination of the EVs optimizing energy costs and energy charging profiles. This proposal considers EV's battery health constraints and mobility constraints and promotes spars day-ahead charging profiles. The distributed scheme keeps the integrity of the private information of the active agents. The sparsity solution is identified using the *alternating direction method of multipliers*. The model proposed alternates between promoting sparsity of the charging profile accomplishing EV's constraints and minimizing energy cost. We assume a decentralized communication between the participants of the optimization problem, exchanging adequate signal prices and power profiles keeping the integrity of the private information of each active agent.**

***Index Terms*—Demand response, Actives agents on the electricity market, Smart Charge for Electric Vehicles**

## I. INTRODUCTION

The electricity generation throughout the world is shifting from fuel-based resources towards a sustainable generation of electricity using solar energy and wind farms. In this sense, the power system is in a state of transition due to the increased amount of renewable-based distributed energy resources (DERs) emerging on the demand-side of the grid [2]. DERs include renewable technology such as solar photovoltaic systems, wind generations, but also encompass other resource capacities such as demand response (DR) programs, batteries, fleet of electric vehicles, and big consumers with flexible load [3], [5]. The Integration of these new technology resources into existing infrastructure and energy markets pose great challenges for power systems as the grid operators usually do not have the appropriate mechanisms for monitoring or controlling distribution networks, which is typically where these resources are connected [3].Besides this technological changes, electricity markets are undergoing an institutional transition. To enhance economic efficiency and improve services to the consumer, the electricity markets have being liberalized gradually, leading to the introduction of competition and opening in the wholesale markets first, and more slowly in the retail market.

From the demand-side point of view, the evolution of the energy sector under the paradigm of smart grids is enabling the interaction between end-users and grid operators. Smart electricity network, or *smart grid*, refers to a electrical grid that includes operation and management features to improve the controlling of production and distribution of energy [4]. Smart grids are the current state-of-the-art technology for electricity networks, the last step in their evolution from unidirectional systems of electric power transmission and distribution to holistic approaches that provide different services for demand-driven control. The main goal of the smart grid is to maintain a reliable, resilient and secure infrastructure to properly satisfy the demand growth and the integration of distributed energy resources [5], [8].

Under the smart grid framework and through different demand response programs, end-users plays a major role as prosumers (consumer/producer) [4], [6], changing its actual passive role to active in the system. In order to absorb the energy that is produced at a certain instant time, an end-user need to allow the adjustment of the working periods of the electrical appliances (smart appliances, battery storage, PV-panels, electric vehicle, etc). This can be done through manual control of each equipment or preferably through an Energy Management System (EMS). EMS perform the control and automation of the electrical appliances, reducing user intervention by running an optimization algorithm that decide when the electrical devices should work. This algorithm should take into account several factors, not only power system status but also end-user preferences in comfort and electrical devices constraints with the main objectives of minimize energy cost or maximize profits.

In this sense, EVs can become integral parts of the smart grid paradigm, since they are capable of providing valuable services to power systems other than just consuming power. On the transmission system level, electric vehicles are regarded as an important means of balancing the intermittent renewable energy resources such as wind power, absorbing the energy during the period of surplus. However, on the distribution system level, the extra loads created by the increasing number of electric vehicles may have adverse impacts on the grid that

[1]The term smart charging is used to describe the uni-directional use of an EV, where the EV is only used as storage (G2V).

Table I: Nomeclature

| | |
|---|---|
| $\mathbf{N}_{ev}$ | Set of EVs participating in the program |
| $\mathbf{x}_{n,t}$ | Charging rate of EV n time t |
| $\mathbf{e}_{n,t}$ | Discharging rate of EV n at time t |
| $S_{n,t}$ | State of Charge (SoC) of EV n at time t |
| $B_n$ | Battery capacity of EV n |

have to be address. As an example, the uncoordinated charging of EV bring new challenges to the power system operators as it cause power flow fluctuation and even generating peaks due to fix time-of-use tariffs. To ensure the stability of the power system, plug-in charging should be coordinated against the bulk power system, including the base load in the distribution system, the stability of the transmission and distribution grid, and the power generation costs. Nevertheless, is unthinkable that each end-user, through its EMS, coordinate with the grid operator the scheduling of their electrical appliances, and also the efficiency of the wholesale market would be affected. Is in this sense where the natural solution is the aggregation of several end-user working in a coordinated manner. Aggregation could be defined as the act of grouping distinct agents in a power system (i.e. consumers, prosumers, or any mix thereof) to act as a single entity when engaging in power system markets (both wholesale and retail) or selling services to the system or grid operators [7].

In this article, we provide a proof of concept realization of the proposed demand response scheme described in [1], modelling an EV-aggregator offering smart charging coordination services to several EVs. In [1], we describe a demand side management (DSM) scheme formulated as an optimal power flow (OPF) problem with several energy retail companies exchanging dynamic information (e.g. power profiles and dynamic prices) with their customers and the grid operator. Particularly, in this work we propose a sparsity-promoting and distributed charging control model coordination. We show that the ADMM [14] provides an effective tool for the design of sparse distributed charge profiles for the EV fleet. This method alternates between promoting the sparsity of the charging profile and optimizing energy costs. The main advantage of this alternating mechanism is twofold. First, it provides a flexible framework for incorporation of different penalty functions that promote sparsity or block sparsity. Second, it allows us to exploit the separability of the sparsity-promoting penalty functions and to decompose the corresponding optimization problems into sub-problems that can be solved distributed.

We assume a decentralized communication between the participants of the optimization problem, exchanging adequate signal prices and power profiles.

The rest of the paper is organized as follow. We introduce the system model in Section II and propose the smart charge control in Section III. Simulation results and discussion are presented in IV and final conclusion in Section V.

## II. Problem formulation and system model

This section describes the problem formulation of the smart charging service provided by the EV-aggregator. We give an overview of the EV's and the aggregator model. The distributed DSM scheme use a discrete-time model with a finite horizon that describes the next twenty four operating hours. Each operational day is divided in $T$ periods of equal duration, indexed by $t \in \mathscr{T} = \{1, .., T\}$. The program considered retails companies only participating in day-ahead market; it does not cover real-time balancing market or auxiliary services such as regulation or reserves.

The $l_1$ norm is widely used as a proxy for cardinality minimization: in applied statistics in: sparse signal processing, machine learning, controls community, etc; see [9], [10], [13], [15]. By gradually increasing the weight on the sparsity-promoting penalty terms, the optimal charging profile moves along a parameterized solution path from the centralized to the sparse profile of interest. This weight is increased until the desired balance between performance and sparsity is achieved.

### A. Electric Vehicle Model

Charging behavior can affect key battery characteristics, such as the state of health, the cycle life and the resistance impedance growth [12], [13]. Furthermore, intermittent charging will shorten the battery lifespan [11]. Therefore, how to decrease the number of charging to maintain battery health is important. On the other hand, a long waiting time to complete a charging task or/and frequent interruptions in the process of charging is unacceptable [13]. Both of them potentially make EV owners discomfort. Recent work [13] shown that consumer's satisfaction is usually characterized by the sparsity of optimal solutions through sparse optimization technique.

We describes the EV's charging constraints based on a piecewise linear function which describes the dynamics of the state of charge (SOC) of the EV's battery. The model is mathematically described as follow [13]:

$$
\begin{aligned}
&S_{n,t+1} = S_{n,t} + \frac{\varrho_n^+ x_{n,t}}{B_n}\Delta t - \frac{e_{n,t}}{\varrho_n^- B_n}\Delta t \\
&S_n^{min} \leq S_{n,t} \leq S_n^{max}
\end{aligned}
$$

where $\varrho_n^-$ and $\varrho_n^+ \in (0,1]$ are the efficiency of charge/discharge of EV $n$ and $B_n$ the maximum capacity of the battery. To prolong the lifespan of the batteries, it is recommended that the values $S_n^{min}$ and $S_n^{max}$ are 15%, and 90%, respectively. After a re-arrange of the previous equation we obtain:

$$
\begin{aligned}
\frac{B_n}{\varrho_n^+ \Delta t}(S_n^{min} - S_n^{init}) + \frac{\varrho_n^-}{\varrho_n^+}\sum_{\tau=1}^{t} e_{n,\tau} \leq \sum_{\tau=1}^{t} x_{n,\tau} \\
\leq \frac{B_n}{\varrho_n^+ \Delta t}(S_n^{max} - S_n^{init}) + \frac{\varrho_n^-}{\varrho_n^+}\sum_{\tau=1}^{t} e_{n,\tau} \qquad (1)
\end{aligned}
$$

being $S_n^{init}$ the initial SOC of the battery in $t = 0$. We denote $I_{n,t} = 1$ if EV $n$ is charged at time $t$, otherwise 0. In practice, we impose the following conservative constraint (see [1], [13]) where every EV $n$ reaches at least the final SOC value, $S_n^{final}$

, at the end of the finite time horizon $T$. Thus, the following constraints should be satisfied:

$$x_{n,t}^{min} \leq x_{n,t} \leq x_{n,t}^{max} \quad (2)$$

$$(1 - I_{n,t}) x_{n,t} = 0 \quad (3)$$

$$\sum_{\tau=1}^{t} x_{n,\tau} \geq \frac{B_n}{\varrho_n^+ \Delta t}(S_n^{final} - S_n^{init}) + \frac{\varrho_n^-}{\varrho_n^+} \sum_{\tau=1}^{t} e_{n,\tau} \quad (4)$$

For notational simplicity, we define the feasible set of EV $n$ as:

$$\mathcal{X}_n := \{x_n \quad | \quad x_n \text{ satisfy } (1-4), n = \{1..N_{EV}\}\} \quad (5)$$

where the operational parameters $x_n^{min/max}, S_n^{min/max}$ and $S_n^{init/final}$ are assumed to be private for each EV and predetermined by external factors such as vehicle type and driving style. Note that the set $\mathcal{X}_n$ defined in (5) is a local constraint, which temporally couples the charging schedules across all the time slots for EV $n$.

The EMS of the EV would promote sparse solution minimizing interruptions. This is achieve by incorporating *sparsity promoting* penalty function in the utility function of the EV, where the added sparsity-promoting terms penalize the number of non zero charging slots. In the absence of sparse-promoting terms, the solution of the minimal energy cost subject to the constraints results in dense charging solution. We used the convex relaxation of the cardinality function $\|\beta\|_0 = \sum_T \mathbb{1}_{\beta_i \neq 0}$. The convex relaxation of this norm is the $l_1$ and the sparse-penalty function is describe as follow:

$$G_n(x_n) = \lambda \|x_n\|_1 = \lambda \sum_{t}^{T} |x_{n,t}| \,. \quad (6)$$

As a results, the EMS incorporated in each EV would minimize the energy cost of charging its battery but minimizing non-zeros charging slots.

## B. EV-Aggregator Model

Aggregation is defined here as the act of grouping distinct agents in a power system (i.e. consumers, producers, prosumers, or any mix thereof) to act as a single entity when engaging in power system markets (both wholesale and retail) or selling services to the system operator(s). In the context of this paper and in [1], "an aggregator is a company who acts as an intermediary between electricity end-users or EV owners and the power system participants (other energy suppliers and the grid operator) who wish to serve these end-users or exploit the services provided by these EVs" [**?**]. Although several differences exist in the details of the proposed EV-aggregator concepts, they are assumed to achieve the same goals in this study, regardless the ownership of the charging equipment. Some of these goals are:

- Guarantee driving needs of the EV owners with optimal management of EV charging, promoting spars power profile for the EV;
- link retail market with wholesale market minimizing operational costs;
- Provide demand response to the power system operators with optimal allocation of EV fleet re-sources.

In this sense, as in [1] the EV aggregator has to decide how much power to procure in the wholesale market for each consumption period $t$ of the operating day. Lets $P_{ev} := (P_{ev}(t); t \in \mathcal{T} = \{1; ...; T\})$ be a non-negative vector variable representing power scheduled or reserved by the aggregator in the wholesale market. Schedule $P_{ev}$ incurs a cost to the aggregator of $C_{ev}(P_{ev}; t)$. The dynamic prices set by the retail company to their customers are a direct consequence of $C_{ev}(P_{ev}; t)$. This function summarizes the cost to at least recover the running costs of supplying aggregate demand, including the payment of the wholesale market. Furthermore, the EV-aggregator must assure the supply to their customers. This is modeled with the following constraint:

$$P_{ev}(t) \geq \sum_{N_{ev}} x_{n,t}$$

The main objective of the EV-aggregator is to minimize operational cost, supply their customers and also promote the coordination achieving sparse charging profile for the next 24 hours.

## III. Demand Side Management Model

We used the proposed dual decomposition method saw in [1] to decouple the couple the power balance constraints in the distribution network as follow:

**DSM as an OPF problem**

$$\min_{(\mathbf{P}_z, \mathbf{p}, \mathbf{y}, \mathbf{r}, \mathbf{q}, \mathbf{x})} \sum_{t=1}^{T} C_{DSO}(\mathbf{x}(t)) + \sum_{z \in \mathcal{Z}} C_{DRz}(\mathbf{P}_z; t) + C_{Agg}(\mathbf{P}_{ev}; t)$$
$$- \sum_{h \in \mathcal{H}} \left[ \sum_{a \in \mathcal{A}_h} U_{ha}(\mathbf{y}_{ha}) + D_h(\mathbf{r}_h) \right] - \sum_{n=1}^{N_{ev}} G_n(\mathbf{x}_n; t) \quad (7)$$

s.t Residential end-user constraints

DSO-OPF constraints, $\forall t \in \mathscr{T}$

Residential energy service provider constraints

$\mathcal{X}_n := \{\mathbf{x}_n \quad | \quad \mathbf{x}_n \text{ satisfy } 1-4, n = \{1..N_{EV}\}\}$

$$\sum_{h \in \mathcal{H}_z} \mathbf{p}_h \leq \mathbf{P}_z, \forall z \in \mathcal{Z}$$

$$\sum_{n \in \mathcal{N}_{ev}} \mathbf{x}_n \leq \mathbf{P}_{ev} \quad \text{EV-aggregator supply constraint}$$

$$\mathbf{p}_i = \mathbf{p}_i^g - \sum_{h \in \mathcal{H}_i} \mathbf{p}_h + \sum_{n \in \mathcal{H}_i} \mathbf{x}_n, \forall i \in \mathcal{N} \setminus \{0\} \quad (8)$$

$$\mathbf{q}_i = \mathbf{q}_i^g - \sum_{h \in \mathcal{H}_z} \mathbf{q}_h + \sum_{n \in \mathcal{H}_i} \mathbf{q}_n, \forall i \in \mathcal{N} \setminus \{0\} \quad (9)$$

$$\sum_{h \in \mathcal{H}} \mathbf{p}_h + \sum_{n \in \mathcal{N}_{ev}} \mathbf{x}_n = \sum_{z \in \mathcal{Z}} \mathbf{P}_z + \mathbf{P}_{ev} - \sum_{(i,j) \in \mathcal{E}} r_{ij} \mathbf{l}_{ij} \quad (10)$$

Constraints (8-10) are the coupling constraints in problem (7), we use a *Lagrange* relaxaction to obtain the following optimization problem for each agent participating in the DSM program (see [1] for more details).

$$\begin{aligned} \min \quad & \sum_{z\in\mathcal{Z}} \mathbb{L}_{com_z}(\cdot;\cdot) + \mathbb{L}_{DSO}(\cdot;\cdot) + \sum_{h\in\mathcal{H}} \mathbb{L}_h(\cdot;\cdot) \\ & \quad + \quad \mathbb{L}_{EV+Agg}(\mathbf{P}_{ev}, \mathbf{x}_n; \sigma, \mu_i) \\ \text{s.t} \quad & (16), \quad \text{Individual agents constraints} \end{aligned}$$

where $\mathbb{L}_{EV+Agg}(\mathbf{P}_{ev}, \mathbf{x}_n; \sigma, \mu_i)$ is the scheduling problem which the EV-aggregator needs to solve and $\sigma$ and $\mu_i$ are the marginal energy cost and the locational cost in bus $i$ imposed by the grid operator. In this case, the aggregator seeks to minimize its operational cost (cost of energy) while improving the satisfaction of their customers, subject to the constraints of each EV charging.

In principle, three types of control strategies can be used by an EV-aggregator when aiming at the objectives mentioned above, namely centralized control, decentralized control considering the distinctive market-based/transactive control and price control, respectively. In this context, it seems almost unthinkable to solved this coordination problem with a centralize control strategy because of the poor scalability of the problem and the private information involved. As a result, we developed a distributed algorithm using the *alternating direction method of multiplayer* where each EV minimize its energy cost and schedule its sparse charging profile based on the dynamic prices sent by the aggregator and its mobility constraints.

### A. Distributed smart charge scheduling promoting sparse solutions

The social welfare problem (7) can be decouple into several sub-problem to be resolve by each energy supplier but coordinated by the grid operator. As a result, EV-aggregator scheduling problem is defined as:

$$\begin{aligned} \mathbb{L}_{EV+Agg}(\mathbf{P}_{ev}, \mathbf{x}_n; \sigma, \mu_i) &= C_{Agg}(\mathbf{P}_{ev}; t) - \sum_{n=1}^{N_{ev}} G_n(\mathbf{x}_n; t) \\ & -\sigma^T \cdot (\mathbf{P}_{Agg} - \sum_{ev} \mathbf{x}_n) + \sum_{ev} \mu_i^T \cdot \mathbf{x}_n + \lambda_i^T \cdot \mathbf{q}_n \quad (11) \end{aligned}$$

$$\begin{aligned} s.t. \quad & \\ & \text{EVs constraints - Lineal} \\ & \text{Agg Constraints - Lineal} \\ & \sum_{ev} \mathbf{x}_{ev} \leq P_{Agg} \quad \leftarrow \quad \text{Coupling Const}(\epsilon_{ev}) \end{aligned}$$

being $G_n(\mathbf{x}_n; t) = -\lambda \left\|\mathbf{x}_n\right\|_1$ the utility function of each EV. We apply ADMM and a dual decomposition method to decouple the problem of the aggregator and each EV and also distribute the problem of finding a sparse solution for each EV [13], [15].

Lets define:

- $X = \{\mathbf{x}_1; ...; \mathbf{x}_n; P_{EV}\} \in \mathbb{R}^{(N_{EV}+1)\times T}$
- $\mathcal{X}_{n+1} := \{x_{n+1} \quad | \quad x_{n+1} := P_{ev} \geq 0\}$
- $\mathcal{X} = \mathcal{X}_1 \times ... \times \mathcal{X}_n \times \mathcal{X}_{n+1}$
- $\mathcal{I}^{(1)}(X) = \begin{cases} 0, & \text{if } X \in \mathcal{X} \\ +\infty, & \text{if other option} \end{cases}$
- $\mathcal{I}^{(2)}(X) = \begin{cases} 0, & \text{if } \sum_1^{N_{EV}} x_n = x_{n+1} \\ +\infty, & \text{if other option} \end{cases}$
- $F(X) := C_{Agg}(\mathbf{P}_{ev}; t) - (\sigma^T + \epsilon_{ev}) \cdot (\mathbf{P}_{ev} - \sum_{ev} x_n) + \sum_{ev} \mu_i^t \cdot x_n + \mathcal{I}^{(1)}(X) + \mathcal{I}^{(2)}(X)$
- $G(X) := \sum_n^{N_{ev}} \lambda_n \left\|\mathbf{x}_n\right\|_1$

### B. ADMM distributed sparsity-promotion

Consider the following constrained optimization problem:

$$\begin{aligned} \min \quad & F(X) + G(Y) \\ s.t. \quad & X - Y = 0 \quad (\Lambda \rightarrow \text{ Variable Dual}) \end{aligned} \quad (12)$$

which is equivalent to the problem (11) using the definition above. The augmented Lagrangian associated to the constrained problem (12) is given by:

$$L_\rho = F(X) + G(Y) + trace(\Lambda^t(X - Y)) + \frac{\rho}{2}\left\|X - Y\right\|_F^2$$

where $\Lambda$ is the dual variable (i.e., the *Lagrange multiplier*), $\rho$ a positive scalar, and $\left\|\cdot\right\|_F$ is the Frobenius norm. By introducing an additional variable and an additional constraint, we have simplified the problem (11) by decoupling the objective function into two parts that depend on two different variables, $X$ and $Y$. The scalar form of the ADMM problem is as follow:

$$L_\rho = F(X) + G(Y) + \frac{\rho}{2}\left\|X - Y + U\right\|_F^2 - \frac{\rho}{2}\left\|U\right\|_F^2 \quad (13)$$

Where $U = \Lambda/\rho$ is the scaled *Lagrange multiplier*.

In order to find a minimizer of the constrained problem (12), the ADMM algorithm uses the following sequence of iterations:

$$\begin{aligned} X_{k+1} &:= arg\min \mathcal{L}_\rho(X, Y^k, U^k) \quad (14a) \\ Y_{k+1} &:= arg\min \mathcal{L}_\rho(X^{k+1}, G, U^k) \quad (14b) \\ U_{k+1} &:= U^k + X^{k+1} - Y^{k+1} \quad (14c) \end{aligned}$$

until $\left\|X^{k+1} - Y^{k+1}\right\|_F \leq \epsilon_p$ and $\left\|Y^k - Y^{k+1}\right\|_F \leq \epsilon_d$. The ADMM consist in a $X$-minimization step (14a), a $Y$-minimization step (14b) and a dual variable update step (14c).

*1) **X-update** step:*

$$\begin{aligned} X^{k+1} &:= arg\min_X \mathcal{L}_\rho(X, Y^k, U^k) \\ &:= arg\min_X F(X) + \frac{\rho}{2}\left\|X - V^k\right\|_F^2 \\ &:= \min_{X\in\mathcal{X}} \quad C_{Agg}(\mathbf{P}_{ev}; t) - \sigma^T \cdot \mathbf{P}_{ev} \\ & \quad\quad + \sum_{n=ev} (\sigma + \mu_i)^T \cdot x_n + \frac{\rho}{2}\left\|X - V^k\right\|_F^2 \quad (15) \\ & \quad\quad s.t. \quad \sum_{n=1}^{N_{ev}} x_n = x_{n+1} \quad (16) \end{aligned}$$

Since both $F(X)$ and the square of the Frobenius norm can be written as a summation of componentwise functions of a matrix, we can decompose (15) into in $(N+1)$ sub-problems after decoupling (16) and expressed in terms of the individual elements of $X$.

$$x_n^{l+1} = \min_{x_n \in \mathbb{R}^{(1\times T)}} (p_i+\epsilon)^T \cdot x_n + \frac{\rho}{2}\left\|x_n - v_n^k\right\|_2^2 \quad (17)$$
$$s.t. \quad x_n \in \mathcal{X}_n$$
$$x_{n+1}^{l+1} = \min_{P_{ev}} \quad C_{Agg}(\mathbf{P}_{ev};t) - (\sigma+\epsilon)^T \cdot \mathbf{P}_{ev} + \left\|P_{ev} - v_{N+1}^k\right\|_2^2 \quad (18)$$
$$s.t. \quad P_{ev} \geq 0$$
$$\epsilon^{l+1} = \epsilon^l + \alpha_l \dot{(} \sum_n x_n - P_{ev}) \quad (19)$$

where $v^k := y^k + u^k$ and $p_i := \sigma + \mu_i$. Equation (17) is the optimization problem to be solved by the EMS installed in each EV. The fist term in (17) minimize the energy cost for the next day and the second order term search for solution closed to a sparse solution found in the previous $Y$-minimization step. Equation (18) is the optimization problem solved by the aggregator and the dual variable (19) are the 24-shadow prices or marginal prices imposed and updated by the aggregator. As a result we obtain $X^{k+1} = [x_1^*(\epsilon^*),..,x_n^*(\epsilon^*),P_{ev}^*(\epsilon^*)]$ the optimal scheduling profile in step $k$ of the ADMM algorithm.

*2) **Y-update** step:*

$$\begin{aligned} Y^{k+1} &:= arg\min \mathcal{L}_\rho(X^{k+1}, G, U^k) \\ &:= G(Y) + \frac{\rho}{2}\left\|Y - (X^{k+1}+U^k)\right\|_F^2 \\ &:= \sum_n \lambda_n \cdot \|y_n\|_1 + \frac{\rho}{2}\left\|Y - W^k\right\|_F^2 \end{aligned} \quad (20)$$

where $W^k := (X^{k+1} + U^k)$. The $Y$-update problem is also separable in each element of $Y$ resulting in $(N_{ev}+1)$ problems. We define:

$$y_n = \min_{y_n \in \mathbb{R}^{(1\times T)}} \lambda_n \cdot \|y_n\|_1 + \frac{\rho}{2}\left\|y_n - w_n^k\right\|_2^2 \quad (21)$$
$$y_{n+1} = \quad x_{n+1} \quad (22)$$

where the problem $y_n$ is solved by each EMS of the EVs. The EMS solved a least square regularization similar to a *Lasso* problem, finding a sparse solution of the power profile find in the $x_n$-update step.Nevertheless, is important to highlight that the EMS in EV $n$ send to the aggregator the charging profile $x_n^{k+1}$ which is a feasible solution to the their charge constraints. The $y$-update step try to find a sparse solution as closed as possible to the feasible set. The parameter $\lambda$ represents the regularization parameter of the *Lasso* problem.

*3) **U-update** step:*

$$U_{k+1} := U^k + X^{k+1} - Y^{k+1}$$

which is also a separable problem in each component and updated by each EMS d the EVs. Figure 1 shows how and who update each variable and the information exchange between agents. On iteration $k$, in the $X$-update step the aggregator coordinates via signal prices the scheduling problem for the EVs. Once this step converge, each EV seeks in the $Y$-update step for the closed sparse solution to the power profile find in (15). Furthermore, this distributed algorithm preserves the integrity of the private information and converge to an optimal and sparse power profile [14].

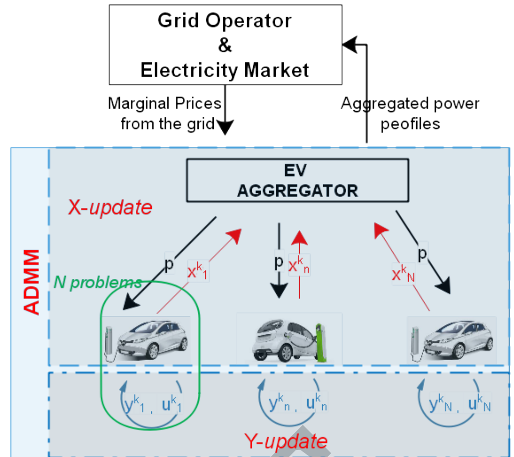
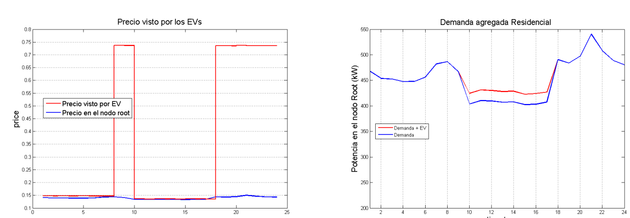



Figure 1: Information Exchange between agents

## IV. Simulations and Results Analysis

We use the same scenario presented in [1] but simulating also the presence of an aggregator providing smart charging strategies to a set of EVs. We consider a scheduling horizon of twenty-four periods of one-hour, starting at 1 A.M. until 12 P.M.. We consider 150 residential end-users and small commercial clients attended by two retail companies and 20 EVs distributed over the grid and coordinated by an aggregator. Residential end-users are not at home during office hours chosen randomly from (07-09) in the morning to (17-20) in the evening. Commercial clients are open from (07-09) in the morning to (18-21) in the evening. We use the IEEE 13-node test feeder as the power distribution system. We assume at least 10 household are connected to each load bus. We assume that each EVs has Incorporated one EMS, which has the information of the mobility constraints and the set of times the EV is plugged to the grid. The maximum power account for each EV is 7kWh. In Figure (2a) we can see in red a cost




(a) ToU tariff proposed by the Aggregator (b) Aggregated demand in node root

Figure 2: Aggregated demand scheduled in the system for the operation day

function of the aggregataor, simulating a ToU tariff for the EVs which promotes valley-filling in the aggregated demand of the system. In (2b) we see in blue the aggregated demand of the residential users and in red the aggregated demand of the EVs. We can appreciate how this cost functions promotes valley filling, maximizing grid performance. In Figure (4), we show

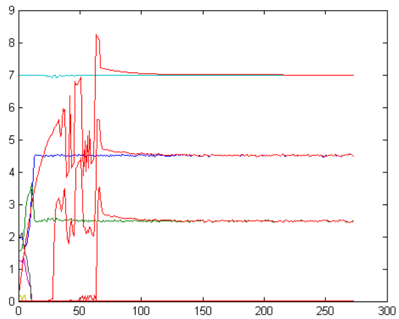
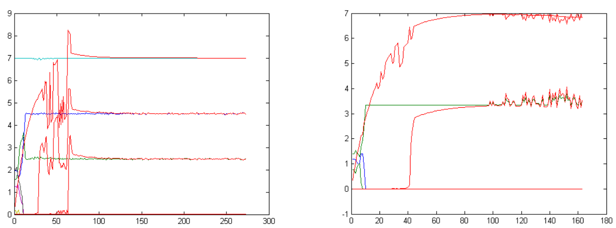


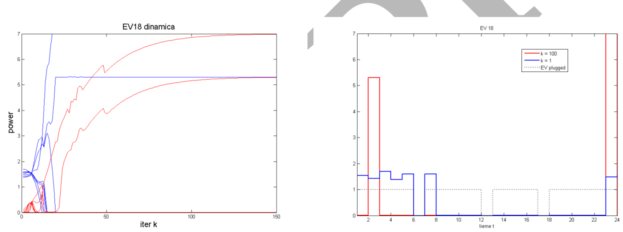
Figure 3: Dynamic of EV #2



(a) Dynamic of EV #15 (b) Dynamic of EV #8

Figure 4: $x - update$ (in color) and $y - update$ (in red) for different EVs plugged along the distribution grid.

the $x$-update step and the $y$-update step iteration for different EVs. The $x$-update in triangles (each time slot is shown in different colors) is the feasible solution to the EV's mobility constraints while the $y$-update (in red color) is the regularize sparse solution closed to the charging profile found in $x$-update step. We can appreciate how after a few iterations the $x$-update reduce the number of charging slots, accomplishing a sparse charging profile in the feasible set. In Figure (5) we can see the




(a) Updates $x^k$ (blue) and $y^k$ (red) (b) Different profile charging

Figure 5: Dynamic of EV #18 and charge profiles

performance of EV #18. In (5a) we appreciate the dynamics of the $x$ (in blue) and $y$-update (in red), similar to the previous figure. We can see that at the beginning of the algorithm we obtain a dense solution in the feasible set. Nevertheless, after a few step and through the coordination of the aggregator, the EV promotes the concentration of the energy in a small set of time slots. This can be more clearly in (5b) where we show in blue a dense solution in the first step of the algorithm and in red line the sparse solution after the algorithm converge.

## V. Conclusion

We model an EV-aggregator offering smart charging coordination services to several EVs under the demand side management framework described in [1]. The model promotes a distributed smart charge coordination of the EVs considering their battery health constraints, mobility constraints and the set of time the EV is plugged to the grid.The sparsity charging profile is identified using the ADMM algorithm which also distribute the problem preserving the private information of each active agent: the first one find a solution for the charging profile of the EV, minimizing energy costs subject to mobility constraints; the second one promote the sparsity of the solution find in step one.

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## References

[1] Montes de Oca, Sebastián and Monzón, Pablo and Belzarena, Pablo, *Demand side management : Optimal demand response in distribution networks with several energy retail companies*, Journal of Engineering for Sustainable Buildings and Cities,Vol 1, pp 1-12, Apr 2020.

[2] Brown, T.; Newell, S.; Spees, K.; Oates, D. International Review of Demand Response Mechanisms The Brattle Group Inc.: Sydney, Australia, 2015.

[3] Bird, L.; Milligan, M.; Lew, D. Integrating Variable Renewable Energy: Challenges and Solutions National Renewable Energy Laboratory: Golden, CO, USA, 2013.

[4] James Momoh. *Smart Grid: Fundamentals of Design and Analysis*. Wiley-IEEE Press, 2012.

[5] Federal Energy Regulatory Commission. Assessment of demand response & advanced metering. Technical Report AD-06-2-00, 2006.

[6] D. Brown ,S. Hall and Mark E. Davis *in the post subsidy era: an exploration of new prosumer business models in the UK*. Energy Policy,Vol 135, 2019

[7] Kody T. Ponds, A. Arefi, A. Sayigh and G. Ledwich. *Aggregator of Demand Response for Renewable Integration and Customer Engagement: Strengths, Weaknesses, Opportunities, and Threats* Energies,Vol 11, 2018.

[8] European Automotive Research Partner Association. Smart Grids European Technology Platform. https://www.etip-snet.eu/. Jan 2020.

[9] Candes, Emmanuel J., Michael B. Wakin, and S Boyd. *Enhancing sparsity by re-weighted 1 minimization.* Journal of Fourier analysis and applications 14(5-6), 2008

[10] Tropp, Joel A. relax: Convex programming methods for subset selection and sparse approximation. In ICES report 404, 2004.

[11] L. Gan, U. Topcu and S. H. Low. *Optimal decentralized protocol for electric vehicle charging* in IEEE Transactions on Power Systems, vol. 28, no. 2, pp. 940-951, 2013.

[12] Z. Ma , S. Zou , X. Liu , *A distributed charging coordination for large-scale plug-in electric vehicles considering battery degradation cost*. IEEE Trans. Control Syst. Technol.Vol 23 (5),2015.

[13] Jueyou Li, Chaojie Li, Zhiyou Wu, Xiangyu Wang, Kok Lay Teo, Changzhi Wu, *Sparsity-promoting distributed charging control for plug-in electric vehicles over distribution networks* Applied Mathematical Modelling,V58, 2018, Pp 111-127.

[14] Boyd, Stephen, et al. *Distributed optimization and statistical learning via the alternating direction method of multipliers.* Foundations and Trends® in Machine learning,Vol 3(1) 2011

[15] F. Lin, M. Fardad and M. R. Jovanović, *Design of Optimal Sparse Feedback Gains via the Alternating Direction Method of Multipliers* in IEEE Transactions on Automatic Control, vol. 58(9), Sept. 2013.