



Delft University of Technology

Energy Management System with PV Power Forecast to Optimally Charge EVs at the Workplace

van der Meer, Dennis; Mouli, Gautham Ram Chandra; Mouli, Germán Morales-España; Elizondo, Laura Ramirez; Bauer, Pavol

DOI

[10.1109/TII.2016.2634624](https://doi.org/10.1109/TII.2016.2634624)

Publication date

2018

Document Version

Final published version

Published in

IEEE Transactions on Industrial Informatics

Citation (APA)

van der Meer, D., Mouli, G. R. C., Mouli, G. M.-E., Elizondo, L. R., & Bauer, P. (2018). Energy Management System with PV Power Forecast to Optimally Charge EVs at the Workplace. *IEEE Transactions on Industrial Informatics*, 14(1), 311-320. Article 7763845. <https://doi.org/10.1109/TII.2016.2634624>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

Green Open Access added to TU Delft Institutional Repository

'You share, we take care!' - Taverne project

<https://www.openaccess.nl/en/you-share-we-take-care>

Otherwise as indicated in the copyright section: the publisher is the copyright holder of this work and the author uses the Dutch legislation to make this work public.

Energy Management System With PV Power Forecast to Optimally Charge EVs at the Workplace

Dennis van der Meer^{ib}, *Student Member, IEEE*, Gautham Ram Chandra Mouli, *Student Member, IEEE*, Germán Morales-España Mouli, *Member, IEEE*, Laura Ramirez Elizondo, *Member, IEEE*, and Pavol Bauer^{ib}, *Senior Member, IEEE*

Abstract—This paper presents the design of an energy management system (EMS) capable of forecasting photovoltaic (PV) power production and optimizing power flows between PV system, grid, and battery electric vehicles (BEVs) at the workplace. The aim is to minimize charging cost while reducing energy demand from the grid by increasing PV self-consumption and consequently increasing sustainability of the BEV fleet. The developed EMS consists of two components: An autoregressive integrated moving average model to predict PV power production and a mixed-integer linear programming framework that optimally allocates power to minimize charging cost. The results show that the developed EMS is able to reduce charging cost significantly, while increasing PV self-consumption and reducing energy consumption from the grid. Furthermore, during a case study analogous to one repeatedly considered in the literature, i.e., dynamic purchase tariff and dynamic feed-in tariff, the EMS reduces charging cost by 118.44% and 427.45% in case of one and two charging points, respectively, when compared to an uncontrolled charging policy.

Index Terms—Autoregressive integrated moving average (ARIMA), electric vehicles, energy management system (EMS), forecast, mixed-integer linear programming (MILP), solar carport.

NOMENCLATURE

Italic letters are used for denoting variables and indexes, whereas regular letters denote parameters and sets.

A. Mixed-Integer Linear Programming

1) Indexes

- c Charging points, running from 1 to C .
- i Electric vehicle, running from 1 to N .
- t Time, running from 1 to T min.

Manuscript received July 30, 2016; revised October 28, 2016; accepted November 27, 2016. Date of publication December 1, 2016; date of current version January 3, 2018. The work of G. Morales-España was supported under the research program URSES, which is partly financed by the Netherlands Organisation for Scientific Research. Paper no. TII-16-0779. (Corresponding author: D. van der Meer.)

The authors are with the Department of DC systems, Energy conversion and Storage, Technical University, Delft 2600, The Netherlands (e-mail: dennis.vandermeer@angstrom.uu.se; G.R.ChandraMouli@tudelft.nl; G.A.MoralesEspaña@tudelft.nl; L.M.RamirezElizondo@tudelft.nl; P.Bauer@tudelft.nl).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TII.2016.2634624

2) System parameters

- η_{inv} Inverter efficiency [p.u.].
- η_{MPPT} DC–DC converter efficiency [p.u.].
- λ_{G2V_t} Marginal purchase price of utility energy during time period t [€/kWh].
- λ_{FIT_t} Feed-in tariff during time period t [€/kWh].
- λ_{PV_t} Marginal price of PV energy during time period t [€/kWh].
- $P_{grid_c}^{+, max}$ Maximum power transfer from the grid to the c th charging point [kW].
- $P_{grid_c}^{-, max}$ Maximum power transfer to the grid from the c th charging point [kW].
- $P_{PV_t}^{max}$ Maximum PV power during time period t [kW].

3) Electric vehicle parameters

- η_{ch}, η_{dis} EV charging and discharging efficiency, respectively [p.u.].
- λ_{deg} Degradation cost of BEV's battery [€/kWh].
- $E_{i,c}^{arrival}$ Energy content of the i th BEV at the c th charging point upon arrival [kWh].
- $E_{i,c}^{departure}$ Energy content of the i th BEV at the c th charging point upon departure [kWh].
- $E_{i,c}^{min}, E_{i,c}^{max}$ Minimum and maximum energy content of the i th BEV at the c th charging point for all time periods t , respectively. [kWh].
- N^{max} Maximum initiations of charging and discharging process [p.u.].
- $P_{ch_i}^{max}, P_{V2G_i}^{max}$ Maximum power transfer to and from the i th BEV, respectively [kW].
- $t_{arrival_i}$ Arrival time of the i th BEV [h].
- $t_{departure_i}$ Departure time of the i th BEV [h].

4) Continuous and positive decision variables

- C_{tot} Total cost incurred from the charging/discharging process [€].
- $E_{i,c,t}$ Energy content of the battery of the i th BEV at the c th charging point during time period t [kWh].
- $P_{V2G_{i,c,t}}$ Power transfer from the i th BEV at the c th charging point during time period t [kW].
- $P_{G2V_{i,c,t}}$ Power transfer to the i th BEV at the c th charging point during time period t [kW].
- $P_{EV_{i,c,t}}$ Total power transfer to the i th BEV at the c th charging point during time period t [kW].

- $P_{\text{grid-EV},i,c,t}^+$ Power transfer from the grid to the i th BEV at the c th charging point during time period t [kW].
- $P_{\text{EV-grid},i,c,t}^-$ Power transfer to the grid from the i th BEV at the c th charging point during time period t [kW].
- $P_{\text{PV-EV},i,c,t}$ Power transfer from the PV system to the i th BEV at the c th charging point during time period t [kW].
- $P_{\text{PV-grid},t}$ Power transfer from the PV system to the grid during time period t [kW].

5) Binary variables

- $D_{i,c,t}^{\text{ch},+}$ Positive difference between ON and OFFstate of binary variable $u_{i,c,t} \{0, 1\}$.
- $D_{i,c,t}^{\text{ch},-}$ Negative difference between ON and OFFstate of binary variable $u_{i,c,t} \{0, 1\}$.
- $D_{i,c,t}^{\text{dis},+}$ Positive difference between ON and OFFstate of binary variable $v_{i,c,t} \{0, 1\}$.
- $D_{i,c,t}^{\text{dis},-}$ Negative difference between ON and OFFstate of binary variable $v_{i,c,t} \{0, 1\}$.
- $s_{i,c,t}$ Binary variable that prevents feeding power into the grid while drawing power from the grid $\{0, 1\}$.
- $u_{i,c,t}$ Binary variable that states whether the i th BEV at the c th charging point during time period t is available for charging (1) or not (0) $\{0, 1\}$.
- $v_{i,c,t}$ Binary variable that states whether the i th BEV at the c th charging point during time period t is discharging (1) or not (0) $\{0, 1\}$.

I. INTRODUCTION

GLOBAL temperature continues to rise, with 2015 currently being the warmest year since measurements began [1]. It is well established that using fossil fuels greatly contributes to CO₂ emissions. More specifically, in the Netherlands, the transport and electricity sectors emit 21.5% and 30% of total CO₂ discharge, respectively [2]. In order to mitigate emissions due to the former sector, electrification of the vehicle fleet is a viable solution. Although battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) can reduce the carbon footprint and increase sustainability of the transport sector, this strongly depends on the generation mix of the electricity with which these are charged [3]. Moreover, even relatively low penetration of PHEVs and BEVs in densely populated areas, such as Amsterdam can already reduce grid reliability due to significant power surges caused by uncontrolled charging [4]. Measures such as price incentives, advances in smart grid technology, e.g., smart charging, and vehicle to grid (V2G) can alleviate stress on the grid and consequently improve reliability of the grid [4], [5]. Furthermore, if source and load are located relatively close to each other, it could also reduce stress on the grid [6].

A. Literature study

Optimization of power flows is an intensely researched topic. Previous studies aimed to minimize emissions [6], to minimize penalty cost [7], [8], to minimize operating cost [9]–[14], to maximize PV self-consumption [15], [16], to improve self-consumption [17], [18], or to maximize profit [19]. The studies

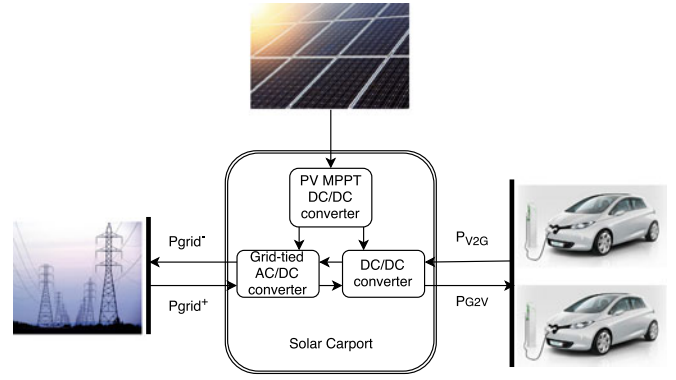


Fig. 1. Schematic representation of the solar carport.

in [6], [11]–[13], [15], [16], [19] achieved satisfactory global optima in terms of their respective objective functions and settings, but performed a day-ahead optimization without forecasting and, except for [15], used a coarse temporal resolution, i.e., 1 h. In [8], an intraday energy management system (EMS) was developed for a residential parking lot that produced promising results, albeit with a coarse temporal resolution and absent of a predictive feature. Further, Chen and Duan [9] and Honarmand *et al.* [10] did include forecasting into their EMSs but did not use these for intraday operation. Additionally, the former study did not attain global optimality. In [7] and [14], the authors developed EMSs that worked on an intraday basis with forecasting capabilities and achieved promising results, albeit local optima. Moreover, the former study was performed with a coarse temporal resolution, while the latter study was performed on a microgrid with many additional distributed generators (DGs) such as fuel cells. Furthermore, the work in [17] and [18], took a different approach through a heuristic strategy and a fuzzy logic controller with forecasting capabilities, respectively. Because of these approaches, global optimality could not have been achieved, however, results presented in [17] showed that self-consumption of PV power increased significantly, whereas results in [18] showed that energy demand from the BEVs were satisfied, while significantly reducing impact on the grid. In addition, their proposed methods allowed high temporal resolution and therefore allowed practical applications.

We propose an EMS that forecasts PV power influx and subsequently optimally plans and allocates power flows at a solar powered workplace parking lot, presented in Fig. 1, with BEVs at a high temporal resolution, with the aim to

- 1) minimize charging cost;
- 2) reduce stress on the main grid;
- 3) increase PV self-consumption;
- 4) increase sustainability of vehicle fleet.

It is important to note that item (3) is realistic because we assume that the marginal price of energy produced by the PV system is less than the price of energy from the grid, which will be elaborated upon in Section IV.

B. Contributions

The main contributions of this paper are as follows: First, the proposed EMS allows us to use a novel modular converter topology as investigated in [20], to which multiple BEVs can

be connected at the same time, which in turn will reduce capital expenditure without the risk of reducing consumer comfort. This is important to stress, since BEV chargers form a substantial portion of the overall system cost. Second, through the inclusion of forecasting capability for PV power production, we can plan power allocation rather than react. Finally, the problem formulation is generic and the charger is modular, and both can therefore readily be extended to a larger scale.

The long time for which BEVs are parked at the workplace offers the possibility to charge these with locally produced PV energy. However, a recent study showed that the average energy transfer at the workplace is 8.53 kWh [21]. Since a 10 kW charger can transfer up to 80 kWh of energy to a BEV during an 8 h workday, we can conclude that the charger will likely not be fully utilized, which in turn reduces the economic performance of the system. In light of the first two contributions, there are at least two approaches to reduce charging costs for BEVs: First, reduce the number of charging points in order to reduce capital expenditure of the overall system. This gives us the opportunity to perform an interesting case study, where we examine the behavior of the proposed EMS in a case when four BEVs are connected to a single charging point. Second, by utilizing inexpensive PV power and dynamic prices in combination with an EMS that can anticipate on both these inputs and plan a charging strategy that minimizes charging cost accordingly.

C. Paper Organization

The paper is organized as follows: Section II describes the modeling approach of the time-series forecast model. Section III formulates the mathematical optimization framework. Section IV specifies the case studies that are used to assess the performance of the proposed EMS. Section V presents the results and compares these to an uncontrolled charging policy, i.e., the status quo. Finally, Section VI presents the conclusions of this research and Section VII presents directions for the future research.

II. TIME-SERIES MODEL FOR PV PRODUCTION

This section presents the time-series model that forecasts PV power production, which will be used as input data for the proposed EMS model.

A. Solar Power Forecasting

Solar power forecasting methods are usually divided into statistical and physical models, where the former are best suitable for intraday forecasts at high spatial resolution, whereas the latter are best suited for day-ahead forecasts with low spatial resolution [22]. Regarding intraday forecasts, Reikard [23] found that autoregressive integrated moving average (ARIMA) models were outperformed by artificial neural networks at the highest temporal resolution, although at the cost of lower spatial resolution. However, Diagne *et al.* [22] concluded that ARIMAs provide the best accuracy in case of forecasting horizons between 5 min and 4 h. Since we work at 1 min temporal resolution and high spatial resolution, the ARIMA class is selected.

TABLE I
PARAMETERS OF THE SARIMA(1, 1, 3) $\times$ (0, 1, 1)₁₄₄₀ MODEL

Parameter	Value
ϕ_1	0.0130
θ_1	-0.0220
θ_2	$8.94 \cdot 10^{-5}$
θ_3	-0.859
Θ	-0.970
Mean	$7.93 \cdot 10^{-9}$
Variance	0.0244

B. ARIMA Process

Box and Jenkins proposed the general ARIMA process and the modeling approach in 1970. This approach consists of three steps and the entire process can be regarded as an iterative process. The three steps are as follows [24]:

- 1) Model identification.
- 2) Model estimation.
- 3) Diagnostic checking.

The ARIMA model consists of two parts: The autoregressive model of order p (AR(p)) and the moving average model of order q (MA(q)), which both describe stationary processes. However, since irradiance data display nonstationary behavior, differencing should be applied to stationarize the time series. In addition, the data of interest can be seasonal, with s time periods, in which case the ARIMA model can be extended to a seasonal ARIMA (SARIMA) model. Introducing B as the backward shift operator, such that $BX_t = X_{t-1}$, the SARIMA model can be expressed in polynomial form as follows:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D X_t = \theta(B)\Theta(B^s)\epsilon_t \quad (1)$$

where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$ describes the nonseasonal AR(p) process with $\phi_1, \dots, \phi_p$ as parameters, and $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$ the nonseasonal MA(q) process with $\theta_1, \dots, \theta_q$ as parameters. A similar approach is taken in case of the seasonal AR(P) and MA(Q) processes. Furthermore, the first difference can be formulated as $(X_t - X_{t-1}) = (1 - B)X_t$ and consequently the d th difference as $(1 - B)^d X_t$. Similarly, seasonal differencing (D) is formulated as $(X_t - X_{t-s}) = (1 - B^s)X_t$ [25]. The SARIMA process is commonly abbreviated as SARIMA(p, d, q) $\times$ (P, D, Q)_s.

C. Results of the Box–Jenkins Approach

Table I presents the parameters of the SARIMA(1, 1, 3) $\times$ (0, 1, 1)₁₄₄₀ model obtained through the Box–Jenkins approach. Since $|\phi_1| < 1$ and the mean is approximately zero, the stationarity condition is satisfied, thus passing the third step, i.e., diagnostic checking. Subsequently, we are able to create an out-of-sample forecast with a 15-min horizon and 1-min resolution. Fig. 2 presents the resulting PV profile of a 10 kW_p array for a sunny day in May 2012. To assess the performance of the

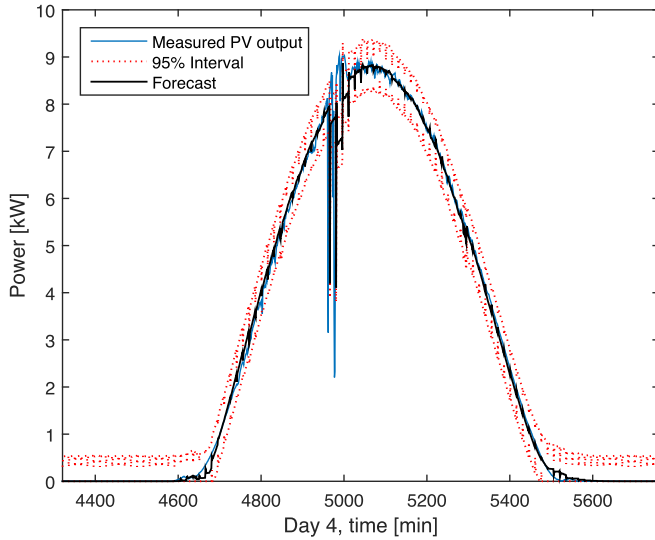


Fig. 2. Out-of-sample forecast with forecast horizon of 15 min.

model, we calculate R^2 and RMSE:

$$R^2 = 1 - \frac{\sum_t (y_{\text{observed},t} - y_{\text{predicted},t})^2}{\sum_t (y_{\text{observed},t} - \bar{y}_{\text{observed}})^2} \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^n (y_{\text{predicted},t} - y_{\text{observed},t})^2}{n}} \quad (3)$$

where y_t represents the value of the time-series at time t , $\bar{y}$ is the mean of the time series, and n is the length of the time-series. R^2 and RMSE amount to 0.986 and 0.395 kW, respectively, and the model is therefore considered suitable for forecasting.

III. MILP MODEL

In this paper, we use a modular converter topology as investigated in [20], which offers four advantages. First, multiple BEVs are allowed to connect to a single charging point, which reduces capital expenditure since fewer charging points have to be implemented. However, since it is physically not possible to charge BEVs connected to the same charging point simultaneously with different charging power, a binary variable is necessary that represents the charging or discharging state of a BEV. Consequently, the problem under consideration is modeled as a mixed-integer program (MIP). Modeling the problem as an MIP gives us the additional advantage to include binary variables, which can be used to keep track of the amount of charging and discharging initializations and protect the batteries of the BEVs connected to the system accordingly.

Although the charging process of batteries is nonlinear, it is common in the literature to approximate it with linear equations, which allows us to formulate the problem as an MILP. The main advantage of formulating our problem as such, also being the second advantage of the proposed EMS, is that although the problem is nonconvex due to the integer variables, the branch and bound algorithm guarantees global optimality nonetheless [26]. For this paper, the MILP is modeled in the general algebraic modeling system and solved by using the CPLEX solver, version 12.6 [27]. Furthermore, we take an aggregated approach in

TABLE II
OVERVIEW OF PARAMETER VALUES

Parameter	Value
η_{ch}	0.90
η_{dis}	0.90
η_{MPPT}	0.98
η_{inv}	0.98
λ_{deg}	€0.038/kWh
λ_{G2V_t}	Dynamic
λ_{FIT_t}	Dynamic
λ_{PV_t}	€/kWh

which the owner of the workplace collaborates with BEV owners, e.g., employer–employee relation, in order to reduce cost and promote BEV ownership.

The third advantage of the proposed EMS is the inclusion of forecasting as introduced in Section II, which allows us to plan power allocation rather than react. Finally, scalability is an important aspect of the project under investigation and the problem formulation presented in this section is therefore kept generic, so that the size of the project can readily be adjusted. Table II presents the parameter values that are used in this paper.

A. Constraints

1) *BEV Constraints:* Each BEV has its own limitation of charging and discharging power:

$$0 \leq P_{\text{G2V}_{i,c,t}} \leq u_{i,c,t} \cdot P_{\text{G2V}_i}^{\max} \quad \forall i, c, t \quad (4)$$

$$0 \leq P_{\text{V2G}_{i,c,t}} \leq v_{i,c,t} \cdot P_{\text{V2G}_i}^{\max} \quad \forall i, c, t. \quad (5)$$

As stated before, it is physically impossible to charge multiple BEVs at the same charging point. In order to reduce cost, we use a modular converter topology as investigated in [20]. Therefore, we need to introduce the following constraint

$$\sum_{i=1}^N u_{i,c,t} + \sum_{i=1}^N v_{i,c,t} \leq 1 \quad \forall c, t. \quad (6)$$

Notice how the two sets of binary variables, $u_{i,c,t}$ and $v_{i,c,t}$, are necessary to guarantee that only one BEV can either charge or discharge in a given charging point during a given period. That is, (6) guarantees that maximum one binary variable can be one, then (4) and (5) force all remaining BEVs cannot neither charge nor discharge.

Due to losses the BEVs receive less power than available at the charging point ($P_{\text{G2V}_{i,c,t}}$). We assume the round trip efficiency for the batteries to be 0.92 [28], and thus, $\sqrt{0.92} = 0.96$ for a single trip. In addition, we assume charger efficiency to be 0.94 [29] and consequently we can calculate that charging/discharging efficiency amounts to $0.96 \cdot 0.94 = 0.90$. The power received by the BEVs can then be calculated according to

$$P_{\text{EV}_{i,c,t}} = \eta_{\text{ch}} \cdot P_{\text{G2V}_{i,c,t}} - \frac{1}{\eta_{\text{dis}}} \cdot P_{\text{V2G}_{i,c,t}} \quad \forall i, c, t. \quad (7)$$

Subsequently, we can calculate energy content of the BEVs:

$$E_{i,c,t} = \begin{cases} 0 & \text{if } t < t_{\text{arrival}_i} \quad \forall i, c \\ E_{i,c}^{\text{arrival}} & \text{if } t = t_{\text{arrival}_i} \quad \forall i, c \\ E_{i,c,t-1} + P_{\text{EV},i,c,t} \cdot \Delta t & \text{if } t_{\text{arrival}_i} < t < t_{\text{departure}_i} \quad \forall i, c \\ E_{i,c}^{\text{departure}} & \text{if } t \geq t_{\text{departure}_i} \quad \forall i, c \end{cases} \quad (8)$$

where BEV owners can define their desired energy content upon departure.

In order to preserve battery life the respective batteries are protected from deep discharges and overcharges through

$$E_{i,c}^{\min} \leq E_{i,c,t} \leq E_{i,c}^{\max} \quad \forall i, c, t. \quad (9)$$

Finally, to reduce the adverse effect that intermittent charging/discharging has on capacity fade [30], we allow the EMS to initiate a maximum of $N^{\max}$ charging/discharging processes as follows:

$$u_{i,c,t} - u_{i,c,t-1} = D_{i,c,t}^{\text{ch},+} - D_{i,c,t}^{\text{ch},-} \quad \forall i, c, t \quad (10)$$

$$v_{i,c,t} - v_{i,c,t-1} = D_{i,c,t}^{\text{dis},+} - D_{i,c,t}^{\text{dis},-} \quad \forall i, c, t \quad (11)$$

$$\sum_{t=1}^T (D_{i,c,t}^{\text{ch},+} + D_{i,c,t}^{\text{ch},-}) \leq N^{\max} \quad \forall i, c \quad (12)$$

$$\sum_{t=1}^T (D_{i,c,t}^{\text{dis},+} + D_{i,c,t}^{\text{dis},-}) \leq N^{\max} \quad \forall i, c. \quad (13)$$

Furthermore, we need to specify when the BEVs are disconnected from the charging point

$$u_{i,c,t} = 0, \quad \text{if } t < t_{\text{arrival}_i} \text{ or } t > t_{\text{departure}_i} \quad \forall i, c \quad (14)$$

$$v_{i,c,t} = 0, \quad \text{if } t < t_{\text{arrival}_i} \text{ or } t > t_{\text{departure}_i} \quad \forall i, c. \quad (15)$$

2) Photovoltaic (PV) System Constraints: The PV system has a rated capacity of 10 kW_p and is equipped with a dc-dc converter with maximum power point tracker (MPPT) that has a European efficiency of 0.98 [31]. Furthermore, in order to allow the EMS to curtail PV power, we introduce the following equation

$$\sum_{c=1}^C \sum_{i=1}^N \frac{1}{\eta_{\text{MPPT}}} \cdot P_{\text{PV-EV},i,c,t} + \frac{1}{\eta_{\text{MPPT}} \cdot \eta_{\text{inv}}} \cdot P_{\text{PV-grid}_t} \leq P_{\text{PV}_t}^{\max} \quad \forall t. \quad (16)$$

3) Grid Constraints: The EV-PV charger is a three-port charger rated at 10 kW [20], [32], [33] and therefore charging and discharging power are limited according to the following equations:

$$0 \leq P_{\text{grid-EV},i,c,t}^+ \leq s_{i,c,t} \cdot P_{\text{grid}_c}^{\max} \quad \forall i, c, t \quad (17)$$

$$P_{\text{EV-grid}_i,c,t}^- + P_{\text{PV-grid}_t} \leq (1 - s_{i,c,t}) \cdot P_{\text{grid}_c}^{\max} \quad \forall i, c, t \quad (18)$$

where the binary variable $s_{i,c,t}$ is imposed on the system to prevent arbitrage.

Finally, we can formulate the power balance that controls the charging process of the BEVs:

$$\begin{aligned} & \sum_{c=1}^C \sum_{i=1}^N (P_{\text{ch},i,c,t} - P_{\text{V2G},i,c,t}) \\ &= \sum_{c=1}^C \sum_{i=1}^N P_{\text{PV-EV},i,c,t} \\ &+ \sum_{c=1}^C \sum_{i=1}^N \left(\eta_{\text{inv}} \cdot P_{\text{grid-EV},i,c,t}^+ - \frac{1}{\eta_{\text{inv}}} \cdot P_{\text{EV-grid}_i,c,t}^- \right) \quad \forall t \end{aligned} \quad (19)$$

where η_{inv} is the grid-tied inverter efficiency. The efficiency of a grid-tied inverter depends on the topology; however, we found 0.98 to be a reasonable value [34].

B. Objective Function

As stated before, the aim is to minimize total cost (C_{tot}) while reducing stress on the grid and increasing PV self-consumption, since 48% of the consumers would likely transition to BEVs because of sustainability concerns, whereas 71% of the consumers would do so for the lower overall cost [35]. Therefore, the optimization problem is formulated such that the aforementioned aspects are considered, which leads to the following objective function

$$\begin{aligned} C_{\text{tot}} = & \left(\sum_{t=1}^T \sum_{c=1}^C \sum_{i=1}^N \lambda_{\text{G2V}_t} \cdot P_{\text{grid-EV},i,c,t}^+ \right. \\ & + \sum_{t=1}^T \sum_{c=1}^C \sum_{i=1}^N \lambda_{\text{PV}_t} \cdot P_{\text{PV-EV},i,c,t} \\ & - \sum_{t=1}^T \sum_{c=1}^C \sum_{i=1}^N (\lambda_{\text{FIT}_t} - \lambda_{\text{deg}}) \cdot P_{\text{EV-grid}_i,c,t}^- \\ & \left. - \sum_{t=1}^T (\lambda_{\text{FIT}_t} - \lambda_{\text{PV}_t}) \cdot P_{\text{PV-grid}_t} \right) \cdot \Delta t. \end{aligned} \quad (20)$$

We can see from the objective function that the EMS indeed works as an aggregated system. It is, however, possible to keep track of individual charging cost and bill the respective owner at the end of the period, e.g., monthly. Furthermore, it is important to stress that the objective function in its presented form is equal to maximizing profits. Finally, Fig. 3 presents the flowchart that depicts the functioning of the proposed EMS.

IV. CASE STUDIES

The effectiveness of the EMS is examined on the basis of two case studies: One and two charging points. Studying one charging point that is fully occupied allows us to ascertain the behavior of the EMS with maximum electricity demand. However, because of the formulation of the EMS, it is also possible for multiple charging points to collaborate in terms of power exchange. For example, if there is a surplus of power production at charging point 1, it could sell this to the grid or complement charging point 2 if needed. Since introducing a second

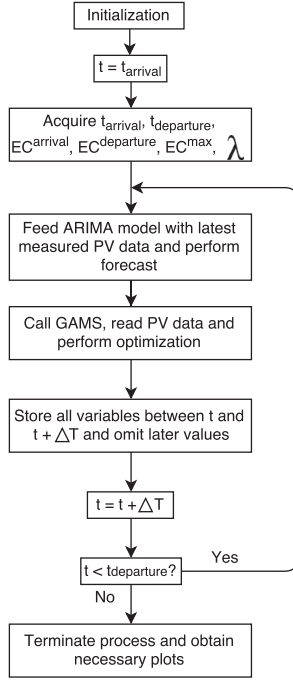


Fig. 3. Flowchart representing the functioning of the EMS.

charging point that is also fully occupied will not display significant collaboration due to high electricity demand, the second case study features an additional charging point that is occupied for 50%, which allows us to show in more detail the collaboration. It should be noted that the behavior of a single, fully occupied charging point can be extrapolated to a larger scale.

Furthermore, the aforementioned case studies are compared to an uncontrolled charging policy. The reason for comparing the proposed model to an uncontrolled charging policy rather than to up-to-date models is twofold: First, the charging methodology in this paper is novel in the sense that a modular converter topology is used, which allows for multiple BEV connections at the same time. Therefore, comparison with up-to-date models cannot be done without modifying those. Second, uncontrolled charging is still the standard in many countries, and hence, a direct comparison between the proposed EMS and the status quo will provide a clear picture on the benefit that one can expect.

Finally, realistic input parameters and appropriate price mechanisms should be selected. It should be noted that we assume these to remain constant throughout the day that is under investigation. This is sufficient for the present study, as the optimization is done for a 24-h cycle, from 00:00 h to 23:59 h. There will be day to day variation in these parameters, and the user is responsible for giving these as an input to the EMS. Therefore, we argue that the characteristics are relatively static on a daily basis. In addition, this paper is a first step into the realization of the proposed EMS, and directions for future research, e.g., stochastic optimization, will be elaborated upon in Section VII.

A. Driving Patterns

Driving patterns of commuters show clear recursive behavior throughout the week. Yearly, the Dutch mobility survey (MON)

TABLE III
ARRIVAL AND DEPARTURE TIME OF DUTCH MOTORISTS

	Arrival	Departure
Average (h)	8.30 A.M.	5.30 P.M.
Standard deviation (h)	1.1	1.1

presents driving patterns of civilians and a study analyzing these patterns, performed in [36], found clear peaks at 8 A.M. and 6 P.M. for morning and evening commute, respectively. Furthermore, these peaks show normal behavior with approximately 1-h standard deviation. Table III presents the exact values of the normal distribution, which are adapted from [18].

B. BEV Specifications

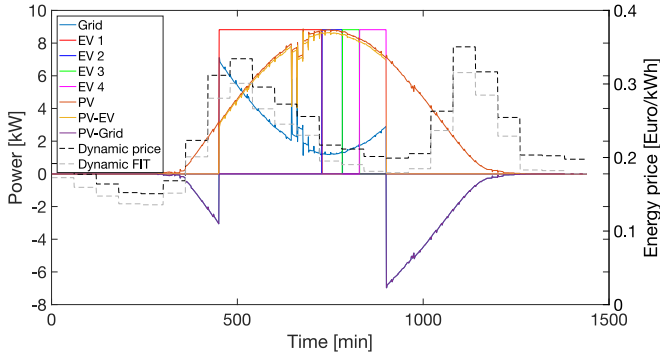
The BEV fleet shows large variation in battery capacity, ranging from 22 to 90 kWh [37]. However, workplace charging tends to be used merely to extend the range of the BEV, with an average energy transfer of 8.53 kWh and standard deviation of 6.49 kWh [21]. Realistic initial and final energy content need to be selected for the case studies, which is often done by using a probability function, e.g., uniform [17], [38] or log-normal [39]. We use a uniform distribution between $0.3 \cdot E_{i,c}^{\max}$ and $0.5 \cdot E_{i,c}^{\max}$ for initial energy content. The required energy stored in the battery upon departure lies between $0.6 \cdot E_{i,c}^{\max}$ and $0.8 \cdot E_{i,c}^{\max}$. Consequently, maximum energy demand by a single BEV will be $(0.8 - 0.3) \cdot 90 \text{ kWh} = 45 \text{ kWh}$ and minimum energy demand by a single BEV will be $(0.6 - 0.5) \cdot 22 \text{ kWh} = 2.2 \text{ kWh}$.

C. Price Mechanism

To ascertain the performance of the proposed EMS, we use both a dynamic purchase tariff (λ_{G2V_i}) and dynamic feed-in tariff (FIT) (λ_{FIT_i}), similar as in [10], [11], and [40]. The purchase tariff is adapted from Amsterdam power exchange [41], to an average of €0.23/kWh. We also assume that the FIT is 10% lower than the purchase tariff, i.e., $\lambda_{FIT_i} = 0.9 \cdot \lambda_{G2V_i}$ [40]. Note that the price mechanism in the additional case studies encompasses a flat purchase tariff of €0.23 /kWh in combination with 1) a flat FIT of €0.23 /kWh or 2) €0.09 /kWh [42]. The reason for this is to examine the performance of the EMS, if it were presently implemented in the Netherlands. In addition, we consider battery degradation due to V2G discharging. Lab experiments regarding capacity loss per normalized Wh have found that this was rather low: $-6.0 \cdot 10^{-3}\%$ for driving tasks and $-2.7 \cdot 10^{-3}\%$ for V2G tasks [30]. However, the authors noted that capacity fade could significantly increase due to intermittent discharging, which is the reason why we introduced (10) and (11). We use € 0.038 /kWh as degradation cost, adapted from [6], which in turn based their findings in [30]. Moreover, this value is similar to that found in [43]. Finally, we defined λ_{PV_i} in the objective function, implying that energy from the PV system is not free. While for the Netherlands, this amounts to € 0.097 /kWh [44], it is usually ignored [10], [11], [45], most likely under the assumption these are sunk cost. Therefore, we assume λ_{PV_i} to be zero, so as to allow for fair comparison.

TABLE IV
INPUT PARAMETERS

	t_{arrival} (a.m.)	$t_{\text{departure}}$ (p.m.)	E_{arrival} (kWh)	$E_{\text{departure}}$ (kWh)
BEV 1	7.31	6.19	29.7	70.2
BEV 2	8.37	7.23	13.8	21.9
BEV 3	7.54	5.17	10.6	17.4
BEV 4	8.50	3.09	10.8	21.3
BEV 5	7.50	4.35	37.5	64.5
BEV 6	9.02	6.59	10.3	23.3

**Fig. 4.** Power allocation with dynamic FIT, 4 BEVs, uncontrolled charging.

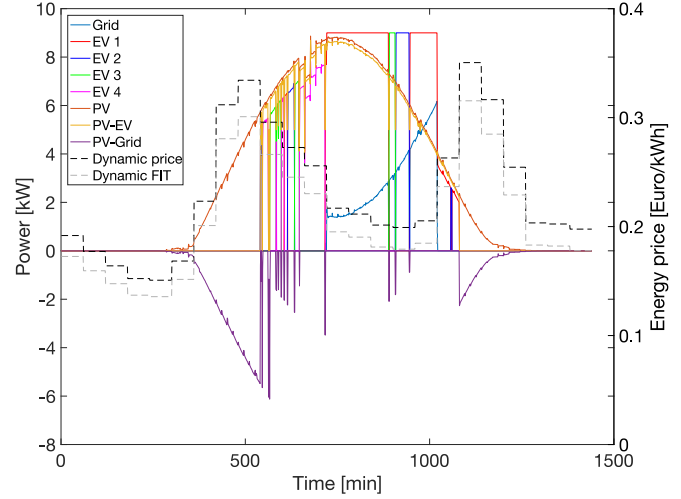
V. RESULTS

Table IV presents the input parameters of the BEVs, resulting from their respective probability distributions. We can deduce from these results that average energy demand amounts to 17.65 kWh, more than double the average demand according to [21]. Furthermore, we impose identical dynamic tariffs on the uncontrolled charging policy, so as to ascertain the true effectiveness of the EMS under such circumstances.

A. One Charging Point

From an economical standpoint, it is more attractive to connect multiple BEVs to a single charger since these are costly. The number of BEVs depends on energy demand, on PV power generation and on converter rating. In this paper, four BEVs are allowed to connect to a single charging point because of the limited converter rating and PV power production, and therefore, increasing the number of connections would likely reduce the effectiveness of the system.

Figs. 4 and 5 present the results of the uncontrolled charging policy and the optimal charging strategy according to the EMS, respectively. There are at least three points of interest. First, power withdrawal from the grid and tariff levels show a similar trend in case of uncontrolled charging, namely a peak during the morning and decrease thereafter. Evidently, this is opposite of what can be considered optimal. In addition, PV power is fed into the grid while λ_{FIT_t} is at its minimum, consequently reducing revenue. Second, we can see from Fig. 5 that the EMS shifts demand away from the peak in morning tariff, while feeding generated PV power into the grid. Therefore, we can conclude that the EMS actively performs demand side

**Fig. 5.** Power allocation with dynamic FIT, 4 BEVs.**TABLE V**
RESULTS ONE CHARGING POINT

	PV self consumption (%)	E_{grid} (kWh)	C_{tot} (€)	Cost reduction (%)
Uncontrolled charging	73.65	39.61	2.181	
Optimal charging	82.41	27.07	-0.4022	118.44

management (DSM) by peak shaving and load shifting. Third, the EMS proves that V2G does not lead to optimality. There is essentially one possibility for V2G, which is during the second peak of λ_{FIT_t} . However, due to the limited time period in which the purchase tariff is low, it is not feasible to charge a BEV beyond its energy requirement, so as to sell it later. Additionally, the surplus of PV power in the morning is immediately fed into the grid, avoiding efficiency losses. Finally, a preliminary case study of our future research, in which ten fully occupied charging points are examined, i.e., 40 BEVs, shows that cost come down from €21.81 to -€4.022.

Table V presents the numerical results of the uncontrolled and optimal charging strategies. PV self-consumption, i.e., the fraction of generated PV power consumed by the BEVs, has been increased from 73.65% to 82.41%. Additionally, energy exchange with the grid, defined as $E_{\text{grid}} = \sum_t \sum_c \sum_i (P_{\text{grid-EV}_{i,c,t}}^+ + P_{\text{EV-grid}_{i,c,t}}^- + P_{\text{PV-grid}_t}) \cdot \Delta t$, was reduced by 31.66%. Furthermore, total cost has been reduced by 118.44%, thus turning cost into profit.

B. Two Charging Points

As stated before, the present case study will investigate the effect on collaboration when a second charging point is introduced that is occupied for 50%, which is a likely scenario during, e.g., vacation periods. As a consequence, there will likely be a surplus of PV power and since the EMS is formulated, such that it allows collaboration as long as that is optimal, we can assess

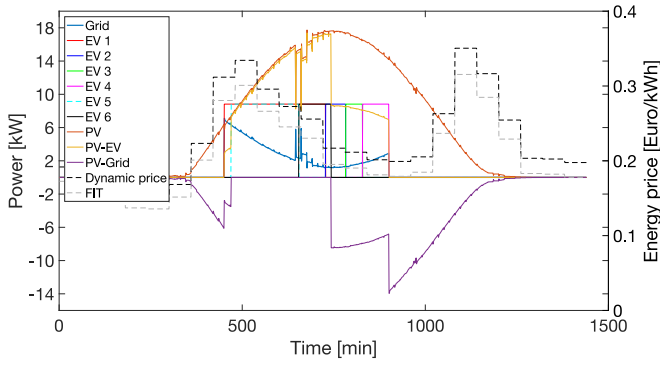


Fig. 6. Power allocation with dynamic FIT, 6 BEVs, uncontrolled charging.

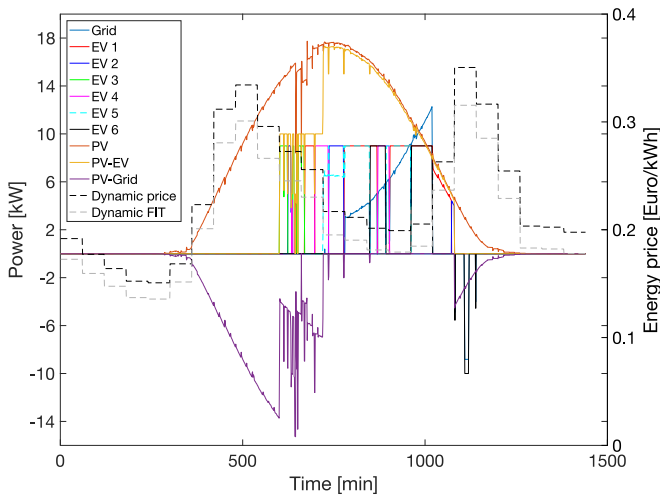


Fig. 7. Power allocation with dynamic FIT, 6 BEVs.

whether or not the overproducing charging point can complement the fully occupied charging point.

Figs. 6 and 7 present the power allocation during the uncontrolled charging policy and optimal charging strategy, respectively. In both cases, we can see similar patterns as in the previous section, i.e., power withdrawal from the grid during peak price and power feed into the grid when λ_{FIT} has significantly lowered in case of the uncontrolled charging policy, whereas the EMS shows that the optimal charging strategy is to shift demand away from peak price period while feeding PV power into the grid during this peak. Furthermore, the EMS does let BEV 6 participate in V2G during the evening peak in FIT. The EMS stores energy in BEV 6, which is connected to the semioccupied charging point, so as to feed it back into the grid during peak FIT. This is accompanied by additional charging/discharging losses however, it is more profitable than feeding PV power directly into the grid during the afternoon, even when taking battery degradation into account. Furthermore, Fig. 7 shows that there are instances in time that there is collaboration between the charging points, however, due to additional losses and high FIT this can lead to suboptimal performance, and is therefore limited to time periods when FIT is relatively low.

Table VI presents the numerical results, from which we can see that self-consumption increased from 58.04% to 66.32%,

TABLE VI
RESULTS TWO CHARGING POINTS

	PV self-consumption (%)	E_{grid} (kWh)	C_{tot} (€)	Cost reduction (%)
Uncontrolled charging	58.04	94.24	-1.468	
Optimal charging	66.32	75.20	-7.743	427.45

TABLE VII
RESULTS FLAT TARIFFS, ONE CHARGING POINT

	FIT (€/kWh)	PV self cons. (%)	E_{grid} (kWh)	C_{tot} (€)	Cost reduction (%)
Uncontrolled charging	0.23	73.65	39.61	0.7538	
Optimal charging	0.23	95.80	7.986	0.4877	35.30
Uncontrolled charging	0.09	73.65	39.61	3.297	
Optimal charging	0.09	95.80	7.986	0.8983	72.75

TABLE VIII
RESULTS FLAT TARIFFS, TWO CHARGING POINTS

	FIT (€/kWh)	PV self Cons. (%)	E_{grid} (kWh)	C_{tot} (€)	Cost reduction (%)
Uncontrolled charging	0.23	58.04	94.24	-5.071	
Optimal charging	0.23	82.56	24.36	-5.603	10.49
Uncontrolled charging	0.09	58.04	94.24	3.069	
Optimal charging	0.09	82.56	24.36	-2.193	171.46

whereas energy exchange with the grid was reduced by 20.20%. Furthermore, profit has increased by 427.45%. This notable result is mainly due to the ability to shift demand away from the peak in purchase tariff and cooperation between the charging points.

C. Additional Case Studies

Here, we examine the performance of the EMS if it were presently implemented, i.e., with flat tariffs rather than dynamic tariffs. Tables VII and VIII present the results, for one and two charging points, respectively. The following two points can be observed. First, cost reduction is more notable in case of a lower FIT. Specifically, the EMS reduces charging cost by 72.75% and 171.46% in case of a FIT of €0.09 /kWh and one and two charging points, respectively, versus 35.30% and 10.49% in case of a FIT of €0.23 /kWh. The reason for this is that in both cases, a significant portion of PV power is fed into the grid but yields less due to a substantially lower FIT. This result shows that high FITs are concealing the true potential of the EMS. Second, a sensitivity analysis in which E_{grid} was minimized showed that the self-consumption in these case studies are maximal, implying that flat tariffs encourage the EMS to maximize self-consumption.

VI. CONCLUSION

In this paper, we proposed a forecasting enabled EMS in a MILP framework, which allows it to plan power allocation in 15-min. periods while taking dynamic tariffs into account. The

aim was to minimize total cost while reducing stress on the grid and increasing PV self-consumption, and consequently increasing sustainability of the vehicle fleet. The model was developed considering a modular converter topology, which allowed us to connect multiple BEVs to a single charging point while one BEV could be charged during a certain time period. In this way, capital expenditure could be reduced when compared to the case when each BEV would require its own charging point. We showed that for these case studies the EMS significantly reduced total cost while reducing energy exchange with the grid and increasing self-consumption, while satisfying energy demand and consequently maintaining consumer comfort. More specifically, in case of one charging point, total cost was reduced by 118.44%, whereas profit was increased by 427.45% when two charging points were considered. Furthermore, due to participating in DSM, self-consumption was increased. Additional case studies showed that if the EMS would be implemented with flat tariffs, it would reduce cost between 10.49% and 171.46%, while high feed-in tariffs (FITs) conceal the effectiveness of the EMS. A preliminary case study of our future research with ten charging points showed similar results, meaning that the EMS can indeed be scaled up. Additionally, its predictive capability enabled the EMS to anticipate on future PV generation, which proved to be vital for its effectiveness. In terms of forecast accuracy the EMS performed satisfactory, achieving an R^2 , of 0.986 and RMSE of 0.395 kW.

In addition, we found that in the presented setting, V2G is currently not economically viable due to battery degradation costs, except in case of a significant surplus of PV power production. For V2G to become attractive, battery prices have to decrease significantly.

Finally, it should be noted that the case study presented in this paper is one of many applications that the EMS could be used for. As we showed with the preliminary, i.e., scaled up, case study, the EMS can be readily extended to a larger scale. In addition, one might think of adding additional DGs and loads as case study, thus emulating a smart grid, in which the EMS can ensure stability and consumer satisfaction.

VII. FUTURE RESEARCH

The following step in our research is to introduce a stochastic optimization framework, where parking times and electricity demand from the BEVs are considered to be uncertain. Furthermore, as the output of any PV system is inherently uncertain, probabilistic PV power production forecasting should be considered. By incorporating these uncertainties, we can find the optimal charging strategy under highly variable circumstances. In addition, modularity of the charger and the generic problem formulation presented in this paper will allow us to increase the scale of the BEV fleet under consideration.

REFERENCES

- [1] NASA/GISS, "Global land-ocean temperature index," 2016. [Online]. Available: http://data.giss.nasa.gov/gistemp/tabledata_v3/GLB.Ts+dSST.txt. Accessed on: Aug. 18, 2016.
- [2] Compendium voor de Leefomgeving, "Emissies broeikasgassen, 1990–2014," Compendium voor de Leefomgeving, Tech. Rep., 2014.
- [3] K. H. Jansen, T. M. Brown, and G. S. Samuelsen, "Emissions impacts of plug-in hybrid electric vehicle deployment on the U.S. western grid," *J. Power Sources*, vol. 195, no. 16, pp. 5409–5416, 2010.
- [4] J. W. Eising, T. van Onna, and F. Alkemade, "Towards smart grids: Identifying the risks that arise from the integration of energy and transport supply chains," *Appl. Energy*, vol. 123, no. 2014, pp. 448–455, 2014.
- [5] F. Mwasilu, J. J. Justo, E. K. Kim, T. D. Do, and J. W. Jung, "Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration," *Renewable Sustain. Energy Rev.*, vol. 34, pp. 501–516, 2014.
- [6] R. A. Verzijlbergh, M. D. Ilic, and Z. Lukszo, "The role of electric vehicles on a Green Island," in *Proc. North Amer. Power Symp.*, Aug. 4–6, 2011, pp. 1–7.
- [7] M. Ghofrani, A. Arabali, and M. Ghayekhloo, "Optimal charging/discharging of grid-enabled electric vehicles for predictability enhancement of PV generation," *Elect. Power Syst. Res.*, vol. 117, pp. 134–142, 2014.
- [8] P. Sanchez-Martin, S. Lumbreras, and A. Alberdi-Alen, "Stochastic programming applied to EV charging points for energy and reserve service markets," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 198–205, Jan. 2016.
- [9] C. Chen and S. Duan, "Optimal integration of plug-in hybrid electric vehicles in microgrids," *IEEE Trans. Ind. Informat.*, vol. 10, no. 3, pp. 1917–1926, Aug. 2014.
- [10] M. Honarmand, A. Zakariazadeh, and S. Jadid, "Integrated scheduling of renewable generation and electric vehicles parking lot in a smart microgrid," *Energy Convers. Manage.*, vol. 86, pp. 745–755, 2014.
- [11] P. T. Baboli, S. Bahramara, M. P. Moghaddam, and M. R. Haghifam, "A mixed-integer linear model for optimal operation of hybrid AC-DC microgrid considering renewable energy resources and PHEVs," in *Proc. 2015 IEEE Eindhoven PowerTech*, 2015, pp. 1–5.
- [12] Y. Li, R. Kaewpuang, P. Wang, D. Niyato, and Z. Han, "An energy efficient solution: Integrating plug-in hybrid electric vehicle in smart grid with renewable energy," in *Proc. 2012 IEEE Conf. Comput. Commun. Workshops*, 2012, pp. 73–78.
- [13] F. Huang, P. Sarikprueck, Y. Cheng, and W.-J. Lee, "Design optimization of PHEV charging station," in *Proc. 2012 IEEE/IAS 48th Ind. Commercial Power Syst. Tech. Conf.*, 2012, pp. 2–8.
- [14] S. Bracco, F. Delfino, F. Pampararo, M. Robba, and M. Rossi, "A dynamic optimization-based architecture for polygeneration microgrids with tri-generation, renewables, storage systems and electrical vehicles," *Energy Convers. Manage.*, vol. 96, pp. 511–520, 2015.
- [15] M. van der Kam and W. van Sark, "Smart charging of electric vehicles with photovoltaic power and vehicle-to-grid technology in a microgrid; a case study," *Appl. Energy*, vol. 152, pp. 20–30, 2015.
- [16] P. J. Tulpule, V. Marano, S. Yurkovich, and G. Rizzoni, "Economic and environmental impacts of a PV powered workplace parking garage charging station," *Appl. Energy*, vol. 108, pp. 323–332, 2013.
- [17] N. Liu *et al.*, "A heuristic operation strategy for commercial building microgrids containing EVs and PV system," *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2560–2570, Apr. 2015.
- [18] T. Ma and O. Mohammed, "Optimal charging of plug-in electric vehicles for a car-park infrastructure," *IEEE Trans. Ind. Appl.*, vol. 50, no. 4, pp. 2323–2330, Jul./Aug. 2014.
- [19] Y. Guo, J. Hu, and W. Su, "Stochastic optimization for economic operation of plug-in electric vehicle charging stations at a municipal parking deck integrated with on-site renewable energy generation," in *Proc. IEEE Transp. Electrification Conf. Expo*, 2014, pp. 1–6.
- [20] G. R. Chandra Mouli, P. Bauer, and M. Zeman, "Comparison of system architecture and converter topology for a solar powered electric vehicle charging station," *Proc. 9th Int. Conf. Power Electron. ECCE Asia*, 2015, pp. 1908–1915.
- [21] I. S. Bayram, V. Zamani, R. Hanna, and J. Kleissl, "On the evaluation of plug-in electric vehicle data of a campus charging network," in *Proc. IEEE Int. Energy Conf.*, 2016, pp. 1–6.
- [22] M. Diagne, M. David, P. Lauret, J. Boland, and N. Schmutz, "Review of solar irradiance forecasting methods and a proposition for small-scale insular grids," *Renewable Sustain. Energy Rev.*, vol. 27, pp. 65–76, 2013.
- [23] G. Reikard, "Predicting solar radiation at high resolutions: A comparison of time series forecasts," *Solar Energy*, vol. 83, no. 3, pp. 342–349, 2009.
- [24] G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, *Time Series Analysis: Forecasting and Control*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1994.
- [25] C. Chatfield, *Time-Series Forecasting*. Bath, U.K.: CRC Press, 2000.
- [26] L. A. Wolsey, *Integer Programming*. New York, NY, USA: Wiley, 1998.
- [27] IBM, "IBM ILOG CPLEX optimization studio," Tech. Rep., 2014. [Online]. Available: <http://pic.dhe.ibm.com>

- [28] Tesla, "Daily powerwall home battery," Tech. Rep., 2016.
- [29] ABB, "Electric vehicle charging infrastructure Terra 51 fast charging station," Tech. Rep., 2016.
- [30] S. B. Peterson, J. Apt, and J. Whitacre, "Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization," *J. Power Sources*, vol. 195, no. 8, pp. 2385–2392, 2010.
- [31] SMA, "SUNNY TRIPOWER 60 the best of two worlds," Tech. Rep., 2016.
- [32] G. Chandra Mouli, P. Bauer, and M. Zeman, "System design for a solar powered electric vehicle charging station for workplaces," *Appl. Energy*, vol. 168, pp. 434–443, 2016.
- [33] G. Chandra Mouli, J. Kaptein, P. Bauer, and M. Zeman, "Implementation of dynamic charging and V2X using Chademo and CCS/Combo DC charging standard," in *Proc. 2016 IEEE Transp. Electrification Conf. Expo.*, 2016, pp. 1–6.
- [34] M. Islam, S. Mekhilef, and M. Hasan, "Single phase transformerless inverter topologies for grid-tied photovoltaic system: A review," *Renewable Sustain. Energy Rev.*, vol. 45, pp. 69–86, 2015. doi: 10.1016/j.rser.2015.01.009.
- [35] K. Gyimesi and R. Viswanathan, "The shift to electric vehicles," IBM Institute for Business Value, Tech. Rep., Jun. 2013.
- [36] J. Hari Kumar, "Sizing and charge control strategies for a grid-connected micro-grid with electric vehicles," Technical University Delft, Delft, The Netherlands, Tech. Rep., Jun. 2012.
- [37] RVO, "Cijfers elektrisch vervoer | RVO.nl (Dutch)," 2016. [Online]. Available: <http://www.rvo.nl/onderwerpen/duurzaam-ondernemen/energie-en-milieu-innovaties/elektrisch-rijden/stand-van-zaken/cijfers>. Accessed on: May 22, 2016.
- [38] L. Jian, Y. Zheng, X. Xiao, and C. Chan, "Optimal scheduling for vehicle-to-grid operation with stochastic connection of plug-in electric vehicles to smart grid," *Appl. Energy*, vol. 146, pp. 150–161, 2015.
- [39] W. Su and M.-Y. Chow, "Investigating a large-scale PHEV/PEV parking deck in a smart grid environment," in *Proc. 2011 North Amer. Power Symp.*, 2011, pp. 1–6.
- [40] P. Sánchez-Martín, G. Sánchez, and G. Morales-España, "Direct load control decision model for aggregated EV charging points," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1577–1584, Aug. 2012.
- [41] "APX | Power Spot Exchange - Making Markets Work |," 2016. [Online]. Available: <https://www.apxgroup.com/>. Accessed on: May 22, 2016.
- [42] Fraunhofer Institute for Solar Energy Systems ISE, "Recent facts about photovoltaics in Germany," Tech. Rep., 2016.
- [43] M. A. Ortega-Vazquez, "Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty," *IET Gener., Transm. Distrib.*, vol. 8, no. 6, pp. 1007–1016, 2014.
- [44] G. Chandra Mouli, M. Leendertse, V. Prasanth, P. Bauer, and S. Silvester, "Economic and environmental benefits of a solar powered smart EV charging station for workplaces in the Netherlands," in *Proc. 2016 IEEE Transp. Electrification Conf. Expo.*, 2016, pp. 1–7.
- [45] W. C. Su, J. H. Wang, and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1876–1883, Jul. 2014.



Dennis van der Meer (S'16) received the Bachelor's degree in mechanical engineering and the M.Sc. degree in sustainable energy technology from Delft University of Technology, Delft, The Netherlands, in 2013 and 2016, respectively.

Since July 2016, he has been a Ph.D. Researcher with the Built Environment and Energy Systems Group, Uppsala University, Uppsala, Sweden, where he is developing probabilistic forecasting methods for solar power and electricity consumption. His research interests include

PV systems, forecasting, and optimization.



Gautham Ram Chandra Mouli (S'14) received the Bachelor's degree in electrical and electronics engineering (gold medal) from the National Institute of Technology Trichy, Tiruchirappalli, India, in 2011 and the M.Sc. degree (*cum laude*) in electrical power engineering from the Delft University of Technology, Delft, The Netherlands, in 2013.

Since October 2013, he has been a Ph.D. Researcher under the "Electric vehicle supported PV smart grid" project at Delft University of Technology, where he is developing a smart charging station for electric vehicles powered from solar panels. His research interest includes PV systems, power converters for EV charging and grid integration of distributed generation.

Mr. Chandra Mouli received the best paper prize at the IEEE INDICON Conference 2009, India, and the best poster prize at Erasmus Energy Forum 2016, The Netherlands.



Germán Morales-España (S'10–M'14) received the B.Sc. degree in electrical engineering from the Universidad Industrial de Santander, Bucaramanga, Colombia, in 2007, the M.Sc. degree from the Delft University of Technology (TUDelft), Delft, The Netherlands, in 2010, and the Joint Ph.D. degree from the Universidad Pontificia Comillas, Madrid, Spain, the Royal Institute of Technology, Stockholm, Sweden, and TUDelft, in 2014.

He is currently a Postdoctoral Fellow in the Department of Software and Computer Technology, TUDelft. His research interests include planning, optimization, and power systems operation.



Laura Ramirez Elizondo received the Bachelors degrees in electrical engineering and in music (with a major in piano) from the Universidad de Costa Rica, San Pedro, Costa Rica, and the M.Sc. (Hons.) degree in electrical power engineering from the Delft University of Technology, Delft, The Netherlands, in 2003 and 2007, respectively. From September 2007 to December 2011, she worked on the Ph.D. project.

She is currently an Assistant Professor in the DC Systems, Energy Conversion and Storage group, Delft. She is currently, as an Assistant Professor, involved in the projects STW Perspektief P13-21: Smart Energy Management and Services in Buildings and Grids (SES-BE); KI Switch 2 Smart Grids: Flexible and future power links for smart grids (FLINK); and NWO URSES project: Gaming beyond the Copper Plate. She is the Co-coordinator of the recently awarded ERA-NET SMARTGRID+ project DC SMART: DC Distribution Smart Grids."

Dr. L. Ramirez Elizondo received the Erasmus Energy Science Award in 2013.



Pavol Bauer (SM'07) received the Master's degree in electrical engineering from the Technical University of Kosice, Kosice, Slovakia, in 1985 and the Ph.D. degree in power electronics from the Delft University of Technology, Delft, The Netherlands, in 1995.

He is currently a Full Professor in the Department of Electrical Sustainable Energy, Delft University of Technology, and the Head of the DC Systems, Energy Conversion and Storage group. He has published more than 72 journals and almost 300 conference papers in his field (with H factor Google scholar 30, Web of science 17); he is an author or co-author of eight books, holds four international patents, and organized several tutorials at the international conferences. He is the former Chairman of Benelux IEEE Joint Industry Applications Society, Power Electronics and Power Engineering Society chapter, member of the Power Electronics and Motion Control council, member of the Executive Committee of European Power Electronics Association, and also the member of international steering committee at numerous conferences.