Multi-Commodity Support in Profile Steering

Martijn H. H. Schoot Uiterkamp, Gerwin Hoogsteen, Marco E. T. Gerards, Johann L. Hurink, Gerard J. M. Smit
University of Twente, Department of EEMCS
Enschede, the Netherlands
{m.h.h.schootuiterkamp, g.hoogsteen, m.e.t.gerards, j.l.hurink, g.j.m.smit}@utwente.nl

***Abstract*—The interest in hybrid energy systems that coordinate multiple commodities simultaneously on residential level (e.g., electricity, heat, gas) is increasing. Such systems can benefit from the synergy between energy carriers to improve the overall energy system efficiency. However, dependencies between commodities make optimisation of such a system generally hard. This paper presents a planning-based multi-commodity energy management system that scales linearly with the number of commodities and connected devices. We apply our approach to balance the three phases in a low voltage grid while charging a fleet of electric vehicles. Simulation results show that our approach is capable of balancing the three phases in this network to enhance the delivered power quality. This balancing also results in a decrease of distribution losses of up to 41.2% compared to a control strategy that does not consider multiple commodities and phase balancing.**

***Index Terms*—load management, demand-side management, phase balancing, multi-commodity energy grids**

I. Introduction

Due to the depletion of fossil fuels and their impact on the environment, there is an increasing interest in efficient energy usage and the integration of renewable energy sources (RES) into our energy systems. Many RES are subject to some production unpredictability (e.g., because of weather conditions) and might therefore not be able to supply the required energy at the time it is needed. Distributed energy management (DEM) aims to solve this problem by using the flexibility of distributed energy resources to match supply and demand. To do so, the flexibility of local production (e.g., combined heat and power (CHP)) and consumption (e.g., electric vehicles (EVs)) assets is exploited.

Several flexible assets involve multiple forms of energy (e.g., electricity, heat, gas). However, current research generally focuses on the optimization of only one of these forms, e.g., to meet a certain (part of) electricity demand by a micro-CHP, fed by biogas when available. Such a system may be combined with a heat pump and heat buffer to ensure that the heat demand can be satisfied at all times. With only control over one commodity, the optimization is often done on basis of electricity profiles, such that the heat pump is preferred when abundant electricity is already produced, e.g., by photovoltaic (PV). This excludes a possible optimal combination mix of biogas and electricity usage at certain times. With multi-commodity optimization it is possible to optimize the combination of electricity, heat buffering and consumption of biogas.

A similar problem occurs in phase balancing in the low voltage (LV) grid. Field tests have shown that unbalance between the three phases can lead to serious problems in the future when, e.g., many EVs are connected to the residential grid (see, e.g., [1]). In essence, the three phases can be seen as separate flows of energy (and thus interpreted as separate commodities) that need to be considered jointly in order to balance them.

This paper presents a multi-commodity energy management system that scales linearly with the number of commodities. It is an extension to the profile steering algorithm as presented in [2], which steers the total energy load profile towards a desired profile. Evaluations have shown that the profile steering algorithm performs very well when matching the demand to the availably supply. The approach can also be readily applied to operational control of energy grids in an event-driven setting [3]. Furthermore, due to the structure of the profile steering algorithm, Toersche [4] already suggested that multi-commodity support can be added easily. The added value of multi-commodity profile steering is demonstrated by a use-case which balances the three phases in an unbalanced LV network. The results of this use-case serve as a proof of concept and show the potential of our system for multi-commodity energy management.

The main contributions of this paper are as follows:

- A planning-based multi-commodity management system,
- which scales linearly in the number of commodities, and
- is scalable using device level optimization algorithms.

The remainder of this paper is organized as follows. Section II provides some background on multi-commodity management systems and phase balancing. In Section III, we present our extension of the profile steering approach with multi-commodity support. As a proof of concept, we apply our method to balance the three phase system within the LV grid while charging a fleet of EVs. For this, we consider different scenarios that we discuss in Section IV. We use simulations to evaluate our approach in Section V. Finally, Section VI gives some conclusions.

II. Background

In the context of multi-commodity energy management, hybrid energy systems (HES) can optimize energy streams simultaneously by exploiting the different characteristics of various forms of energy. For example, heat is easier to store in large quantities than electricity, but harder to transport over long distances. The challenge in designing these HES is to find a proper combination of energy converters and carriers that minimizes the losses in the system. As an example, many systems exist that use waste heat of industrial processes for heating houses (see [5] for a survey).

The shift towards HES also resulted in new distributed energy management (DEM) frameworks that support multiple commodities. Molderink et al. [6] introduce a model for such hybrid energy systems with multiple energy carrier streams and devices. Subsequently, this model is used by a three-step approach to optimize the total energy usage of the system using forecasts, planning and real-time control. Another example is the MultiCommodityMatcher [7], which is an extension of the PowerMatcher [8]. This approach uses a double-sided auction for real-time control of a hybrid system with heat and electricity. The MultiCommodityMatcher is tested in a lab environment and compared to two other control systems in [9], where scalability of the system is seen as a positive point. However, scalability here only refers to the number of controllable assets and not to the number of commodities. The bidding function used by this method grows with one dimension per commodity. Furthermore, the system also requires an additional bid for each commodity, leading to an exponential growth in the required communication volume as the number of commodities increases.

The electricity system itself can also be seen as a hybrid system with multiple commodities such as active and reactive power. Weckx et al. [10] have shown that coordinated reactive power control for PV inverters can be used to improve the voltage levels within the grid. Another example of multi-commodity usage within the electricity grid is the three-phase system. Unbalanced LV grids are a rising concern with the integration of more PV and EVs as shown in a field test [1]. Unbalance means that loads are unevenly distributed over the three phases. This effect results in a current flowing through the neutral conductor, which increases the distribution losses. This also results in the effect of neutral-point shifting where the neutral-to-ground voltage increases and the phase-to-neutral voltages of the three phases differ. Therefore, a balanced LV grid is desired to enhance its operation. One way to balance an unbalanced grid is to rearrange the phase connections of households [11], [12]. Significant reductions in voltage unbalance and equalization of load at the transformer are possible with this method. Similar results are achieved by balancing single phase loads by carefully setting up the DEM control hierarchy as shown in [13]. However, these methodologies cannot cope with three-phase loads. A control mechanisms to balance LV grids using three single phase inverters with a common DC bus is presented in [14]. Simulation results for an unbalanced use-case show that this solution is able to restore the balance and thereby improve voltage levels. Furthermore, overall performance is best measured through total grid losses and these are reduced by a staggering 28% compared to the uncoordinated case. One drawback of this method is that a large quadratic optimization problem must be solved to obtain a planning for the EV charging. As a result, their method is less suitable for re-planning and operational control where very fast solution methods are required.

III. Profile steering approach with multi-commodity support

Within this work, we extend an existing energy management approach called *profile steering* (see [2]) with support for multiple commodities. We first briefly introduce the profile steering algorithm for the single commodity case and then extend it to support multiple commodities.

A. Profile steering heuristic

Profile steering aims to flatten load profiles by sending an explicit *desired profile* from one higher-level controller (or *fleet controller*) on, e.g., the neighbourhood level, to multiple lower level controllers or devices on, e.g., the residential level. These profiles express exactly what the higher-level control wants the low-level controllers or devices to achieve. The objective for a low-level controller is to follow this steering signal by minimizing the distance between this *desired profile* and the aggregated *power profile* $\vec{x} = [x_1, \dots, x_N]^T$ of the fleet of devices, with N being the number of time intervals, according to some vector norm. In our case, we use the Euclidean distance (i.e., minimize $||\vec{x} - \vec{p}||_2$). A *desired profile* $\vec{p} = [p_1, \dots, p_N]^T$ could for instance be a zero-profile (i.e. $[0, \dots, 0]^T$) which expresses that a balance of production and consumption of energy is desired.

Initially, each device m receives this *desired profile* $\vec{p}$ and is asked to minimize the distance between this *desired profile* and its own *power profile* $\vec{x}_m = [x_{m,1}, \dots, x_{m,N}]^T$. The higher level controller receives all *power profiles* from connected devices or controllers, resulting in an aggregated *power profile* $\vec{x} = \sum_{m=1}^{M} \vec{x}_m$, with M being the number of devices. Then, in an iterative manner, the controller sends out a *difference profile* $\vec{d} = \vec{x} - \vec{p}$. The devices or lower-level device controllers obtain a local desired profile $\vec{p}_m = \vec{x}_m - \vec{d}$ and respond with a new optimized candidate *power profile* $\vec{\hat{x}}_m$ that minimizes $||\vec{x}_m - \vec{p}_m||_2$. Subsequently, the controller selects the device m with the largest improvement e_m in the objective. The chosen device m commits its own candidate profile (i.e., $\vec{x}_m := \vec{\hat{x}}_m$) and communicates its changes, such that the fleet controller can update $\vec{x}$. Subsequently, a new *difference profile* $\vec{d}$ is obtained to repeat the process until no significant improvement is possible or the maximum number of iterations is reached. The result of the algorithm is a schedule $\vec{x}_m = [x_{m,1}, \dots, x_{m,N}]^T$ for each device m. We refer the reader to [2] for more background on profile steering.

B. Multi-commodity extension

The method described above only considers one commodity over a given planning horizon. We observe that we can easily extend this approach by communicating multiple profiles simultaneously, where each profile represents a commodity. To keep the algorithm generic, we denote the number of commodities with C and the set of commodities with $\mathcal{C} = \{c_1, \dots, c_C\}$. Any profile vector for an individual commodity $c \in \mathcal{C}$ is indicated by a superscript, e.g., $\vec{x}^c = [x_1^c, \dots, x_N^c]^T$ and $\vec{x}_m^c = [x_{m,1}^c, \dots, x_{m,N}^c]^T$. In essence, this means that the original profile vectors from [2] are replaced by profile matrices. Hence, for sake of clarity, we change the previously defined notation for the profiles into capitals, e.g. $\vec{x}$ becomes $\vec{X}$ and $\vec{x}_m$ becomes $\vec{X}_m$. Herein, the rows represent the time intervals and the columns represent commodities, e.g.,

$$\vec{X} = \begin{bmatrix} x_1^{c_1} & x_1^{c_2} & \dots & x_1^{c_C} \\ x_2^{c_1} & x_2^{c_2} & \dots & x_2^{c_C} \\ \vdots & \vdots & \ddots & \vdots \\ x_N^{c_1} & x_N^{c_2} & \dots & x_N^{c_C} \end{bmatrix}, \vec{X}_m = \begin{bmatrix} x_{m,1}^{c_1} & \dots & x_{m,1}^{c_C} \\ x_{m,2}^{c_1} & \dots & x_{m,2}^{c_C} \\ \vdots & \ddots & \vdots \\ x_{m,N}^{c_1} & \dots & x_{m,N}^{c_C} \end{bmatrix}.$$

Instead of minimizing the Euclidean distance between a *power profile* vector and the *desired profile* vector, we now need to do this over all commodities $c \in \mathcal{C}$. Hereby, in certain scenarios, the final profile of one commodity may be more important than the profile of other commodities. Therefore, we introduce weights $W = \{w_1, \dots, w_C\}$, where w_i expresses the preference of the i^{th} commodity. This results in the following general objective:

$$\min \sum_{c=1}^{C} w_c \cdot ||\vec{x}^c - \vec{p}^c||_2. \quad (1)$$

We note that also other optimization objectives are possible for multiple commodities as we will show in Section IV.

Except for the switch from vectors to matrices, nothing significantly changes for the fleet controller. This is due to the fact that the fleet controller only coordinates and does the overall bookkeeping of the profiles, whereas the devices perform the actual optimization. It is likely that each device m can only consume/produce energy for a subset $\mathcal{C}_m \subseteq \mathcal{C}$ of the commodities, hence other commodities can be neglected.

Originally, the improvement e_m by device m was given by the amount it can reduce the distance ($||d||_2$) when offering the load profile $\vec{x}_m$ instead of $\hat{\vec{x}}_m$. In the multi-commodity case, we decompose the overall improvement into multiple improvements e_m^c for each commodity $c \in \mathcal{C}$, that already include the corresponding weight w_c. The fleet controller selects the device with the largest overall improvement $e_m = \sum_{c=1}^{C} e_m^c$. To reduce the data communication, the selected device m should communicate only the candidate profiles of the commodities in $\mathcal{C}_m$. The details of the algorithm are presented in Algorithm 1. Note that this algorithm reduces to the algorithm presented in [2] when $C = 1$ and $W = \{1\}$ are used.

Since the devices determine and communicate the optimal profile themselves, they can directly incorporate local constraints on the dependencies between commodities. Hence, there is no need to communicate these dependencies in contrast to an auction-based approach as presented in [7]. Although local device optimization problems might become harder when multiple commodities are involved and therefore less efficient, the resulting optimization heuristic scales linearly with the number of commodities. So for C commodities, we have at most C times as much data to be communicated per iteration. Furthermore, the original profile steering approach is already scalable by the usage of a hierarchical tree of controllers, which is also the case for the presented extension.

Algorithm 1 Multi-commodity profile steering algorithm.

Request each device $m \in \{1, \dots, M\}$ to minimize $\sum_{c \in \mathcal{C}_m} w_c \cdot ||\vec{x}_m^c - \vec{p}^c||_2$ {Or other distance metric}
$\vec{X} := \sum_{m=1}^{M} \vec{X}_m$ {Total fleet consumption}
repeat
  $\vec{D} := \vec{X} - \vec{P}$ {Difference matrix}
  for $m \in \{1, \dots, M\}$ **do**
    $\vec{P}_m = \vec{X}_m - \vec{D}$
    Find a planning $\hat{\vec{X}}_m$ for device m that minimizes $\sum_{c \in \mathcal{C}_m} w_c \cdot ||\vec{x}^c - \vec{p}^c||_2$ {Or another objective}
    $e_m := 0$
    for $c \in \mathcal{C}_m$ **do**
      $e_m^c = w_c \cdot \left(||\vec{x}_m^c - \vec{p}_m^c||_2 - ||\hat{\vec{x}}_m^c - \vec{p}_m^c||_2 \right)$
      $e_m := e_m + e_m^c$ {Relevant flexibility of m}
    end for
  end for
  Find the device m with the highest contribution e_m
  for $c \in \mathcal{C}_m$ **do**
    $\vec{x}^c := \vec{x}^c - \vec{x}_m^c + \hat{\vec{x}}_m^c$ {Update the total consumption}
    $\vec{x}_m^c := \hat{\vec{x}}_m^c$ {Update the profile of device m}
  end for
until $e_m < \epsilon$ {Repeat if there is sufficient progress}

IV. EV SCHEDULING WITH MULTIPLE PHASES

As a proof of concept, and to show the effectiveness of our approach, we apply multi-commodity profile steering to balance the three-phase system within a LV grid by charging a fleet of EVs. This means that the EVs charge such that they restore the balance and the negative effects of unbalance as outlined in Section II are minimized. In this context, we model each phase as an individual commodity.

An important objective in the context of EV charging is to flatten the overall load profile of a house or neighbourhood as this minimizes distribution losses, voltage fluctuations and reduces the peak loads in the grid. Therefore, we use this objective next to phase balancing. Note that these two objectives do not necessarily coincide, especially when the network itself is already unbalanced. For example, if there is much unbalance between phases in a certain time interval due to a peak load in one phase, then much charging could be scheduled on the other two phases to minimize this unbalance. However, this implies that the resulting total load in this interval will be very high compared to other intervals for which the uncontrollable load on the phases is already balanced and no charging is added for balancing. On the other hand, peak-shaving could lead to large unbalance between phases when the distribution of uncontrollable load amongst phases is not taken into account in this objective.

To study the impact of different types of EV chargers (i.e., single-phase chargers and three-phase chargers) and the two aforementioned objectives of phase balancing and peak-shaving, we study three cases where we apply the profile steering approach with multi-commodity support that we introduced in the previous section:

- **Case *MC-1*.** In this case, we have a single phase charger that can select one of the phases through a controller, for example by using three relays. The controller decides which phase is selected for charging the whole required charging volume. The objective in this case is peak-shaving for this particular phase, i.e., to flatten the profile of this phase.
- **Case *MC-3a*.** In this case, all EV charging stations are equipped with three single-phase inverters with a common DC bus, such that the charger can spread the load asymmetrical over the phases. The objective in this case is phase balancing.
- **Case *MC-3b*.** This case is similar to the case *MC-3a*, but with a different objective, namely peak-shaving. As for peak-shaving the distribution of the EV load over phases does not matter, we first apply peak-shaving and subsequently balance the phases for each time interval, given the load that was optimal according to the peak-shaving objective.

We discuss the underlying optimization problem of each case later in this section.

A fleet controller coordinates the optimization process of multiple EVs to the global objective using the presented profile steering approach. The EV schedules are created individually for each device. Therefore, in the remainder of this section, we restrict ourselves to the planning of a single EV. For this, we introduce some more specific notation. The set $\mathcal{C} = \{1, 2, 3\}$ corresponds to the three phases and, for each $c \in \mathcal{C}$, x_n^c denotes the amount that is charged on phase c in time interval n (this corresponds to the device profile in the previous section). Furthermore, let R be the required charging volume, $\bar{x}$ the maximum charging power of the EV per phase and Δ the length of each time interval.

For the case *MC-1*, each EV can charge at only one of the three phases. Therefore, for each phase, we compute an optimal charging schedule that uses only this phase. After comparing the three resulting schedules, we choose the phase whose schedule yields the largest improvement on the objective value. This means that for each phase $c \in \mathcal{C}$, we minimize (1) with $w_c = 1$ and $w_{c'} = 0$ for $c' \in \mathcal{C}\backslash\{c\}$ subject to the constraints

$$\sum_{n=1}^{N} \Delta x_n^c = R$$

and

$$0 \leq x_n^c \leq \bar{x}, \quad n = 1, \dots N. \tag{2}$$

To simplify the notation, we assume without loss of generality that $\Delta = 1$ in the remainder of this section.

In the case *MC-3a*, we consider all phases to be a commodity and we minimize (1) with equal weights w_c subject to the constraints

$$\sum_{c=1}^{3} \sum_{n=1}^{N} x_n^c = R \tag{3}$$

and the constraints in (2) for each $c \in \mathcal{C}$.

Finally, in case *MC-3b*, we first aim at peak-shaving for the three phases combined. That is, we minimize the difference between the total profile and the desired profile:

$$\min \left\| \sum_{c=1}^{3} (\vec{x}^c - \vec{p}^c) \right\|_2$$

subject to the resource constraint in (3) and the constraints in (2) for each $c \in \mathcal{C}$. Subsequently, we consider each time interval individually and balance the phases given the total load of the interval. This means that, given the vector $\vec{x}^c$, we minimize (1) with equal weights w_c for each time interval n:

$$\min \sum_{c=1}^{3} ||x_n^c - p_n^c||$$

subject to

$$\sum_{c=1}^{3} x_n^c = \sum_{c=1}^{3} \vec{x}_n^c$$

and the constraints in (2) for $c \in \mathcal{C}$ and the given interval n.

All these optimization problems can be rewritten in a form that can be solved using load profile flattening algorithms such as the one in [15]. Since there exist algorithms for these types of problems that run in linear time [16], computing the improvements for all EVs can be done efficiently in all cases.

V. Evaluation

We created a use case to evaluate the added value of multi-commodity support for profile steering. The objective of the use case is to balance the three phases in an unbalanced LV grid that includes locally generated electricity from PV panels by charging EVs. Herein, multi-commodity support in the form of multi-commodity optimization of three separate phases is the only change compared to the single-commodity control. For both single-phase charging (*MC-1*) and three-phase charging (*MC-3a*, *MC-3b*) the impact on the grid is evaluated and compared to charging strategies using a single commodity. The distribution losses are seen as a key performance indicator as both large loads on the grid and unbalance between the phases lead to more distribution losses.

A. Use case

The use case studies a residential neighbourhood with 81 households within the Netherlands. A detailed model of the LV distribution network of this neighbourhood is available to perform load-flow simulations that we use to evaluate the performance of the control strategies on the physical grid. This model contains a four-wire three-phase model of the cables with mutual impedances. These models and the load-flow solver are verified to accurately match the physical network using two field tests [1], [17]. Household load profiles, both static load and PV production, are generated using an artificial load profile generator [18]. The baseload of each house is connected to one of the phases, where the houses are evenly distributed over the three phases. 42 households are equipped with rooftop PV, of which the majority is connected to phase 2 as illustrated by the total PV power consumption per phase in Fig. 1, resulting in unbalance. The balancing flexibility comes from 21 EVs within this grid. Since we only aim at validating our model, we do not use any advanced methods to predict

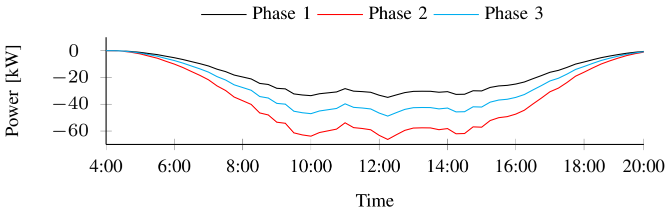

Fig. 1. Spread of PV production over the phases.

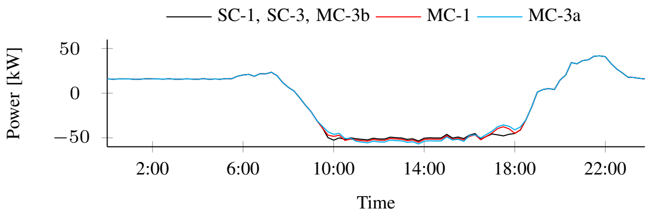

Fig. 2. Power profile after optimization.

when EVs are available but simply assume that each EV is available between 8:30 and 17:30 and needs to charge 15 kWh.

In this use case, we consider two different charging strategies: single-phase and three-phase charging. In case of single-phase charging, we assume a maximum charging rate of 7360 W (= 32 A at 230 V). For the reference single-commodity case, the selected phase is fixed and 10 of the 21 EVs are connected to phase 3, whereas phases 1 and 2 have 6 and 5 EVs respectively. This case is referred to as *SC-1* and we compare it to the multi-commodity case *MC-1*.

For three-phase charging we assume a maximum charging rate of 3680 W (16 A at 230 V) per phase. For the reference single-commodity case, a normal three-phase AC/DC inverter is assumed that spreads its load equally over the three phases. We refer to this case as *SC-3* and compare it to the multi-commodity cases *MC-3a* and *MC-3b*.

To evaluate the performance of the control algorithm itself, we assume perfect information, i.e., no predictions are used but loads are given. A single day is simulated with the interval length set to 1 minute. The planning is done using intervals with a length of 15 minutes. The desired profiles are a balanced production and consumption for the single-commodity case $\vec{p} = [0, \ldots, 0]^T$, and a balance per commodity for the multi-commodity-case, i.e., $\vec{p}^c = [0, \ldots, 0]^T$.

B. Results

Since the EVs are connected between 8:30 and 17:30, flexibility is used only in this time interval and differences can be observed in the overall power profile as depicted in Fig. 2. Table I summarizes the results of the simulations within this time horizon. The used notation is introduced in the next paragraph.

The multi-commodity implementation of the profile steering heuristic outperforms its single-commodity counterpart by a large margin. All the multi-commodity cases (*MC-1*, *MC-3a*, *MC-3b*) show significant improvements on the minimum and maximum voltage levels obtained at a node within the network

TABLE I
NUMERICAL RESULTS OF THE SIMULATIONS BETWEEN 8:30 AND 17:30

	SC-1	*MC-1*	*SC-3*	*MC-3a*	*MC-3b*
Obj. SC ($\cdot 10^9$)	1343	1347	1343	1357	1343
Obj. MC ($\cdot 10^9$)	220	156	201	155	157
$U_{\mathbf{min}}$ (V)	217.7	224.1	223.7	225.7	224.6
$U_{\mathbf{max}}$ (V)	245.3	241.6	244.3	241.2	241.3
$U_{\mathbf{N\text{-}G,max}}$ (V)	10.4	6.2	7.3	5.4	5.4
Max. VUF (%)	1.18	0.74	1.01	0.68	0.72
Max. Util (%)	81.9	57.3	72.6	50.4	57.7
Losses (kWh)	13.07	7.96	10.78	7.16	7.41

(U_{min} and U_{max}). The closer these values are to the nominal 230 V, the better. The balancing is visible in the maximum voltage obtained between neutral and ground ($U_{\text{N-G,max}}$) which is significantly reduced (improved) with the multi-commodity profile steering heuristic (Fig. 3). This also results in a lower maximum Voltage Unbalance Factor (VUF), as defined in the EN-50160 regulations [19], as depicted in Fig. 4. However, no power quality regulations were violated in any case.

Other grid properties also show significant improvements with multi-commodity profile steering. The maximum load on a cable section (Max. Util) within the LV grid is reduced from 81.9% in case *SC-1* to 57.3% in case *MC-1*, Furthermore, we observe a reduction of the maximally used capacity from 72.6% in case *SC-3* to 50.4% in case *MC-3a*. The most important overall performance indicator is the distribution losses. Here we see a decrease of 41.2% for the single phase charging case (from 13.07 kWh in case *SC-1* to 7.96 kWh in case *MC-1*). The three-phase charging case is more balanced by default, but the decrease in losses is also significant here with 33.6% (from 10.78 kWh in case *SC-3* to 7.16 kWh in case *MC-3a*). Also the current measured in the neutral conductor at the transformer is a good indicator for the unbalance. The multi-commodity cases show that this current is strongly reduced and is nearly zero as is desirable (see Fig. 5).

The total power consumption $\vec{s}$ and power consumption per commodity $\vec{s}^c$ are obtained from the simulations in intervals with one-minute length. Based on these results, we can evaluate how good the solutions score on the original objectives. Herein *Obj. SC* is the original objective of minimizing the Euclidean distance ($\min ||\vec{s} - \vec{p}||_2$). For the multi-commodity balancing (*Obj. MC*) we evaluate the general objective as introduced in Section III ($\min \sum_{c=1}^{C} w_c ||\vec{s}^c - \vec{p}^c||_2$). The results in Table I indicate that the method in case *MC-3a* performs best at the latter objective. This in contrast to *MC-3b*, which first optimizes towards overall peak-shaving. As a result, the overall single-commodity objective value for *MC-3b* exactly matches that of the single-commodity approach in *SC-1* and *SC-3*. This results in a slightly less balanced grid, but the differences are very small. Noteworthy is the good performance achieved in case *MC-1*, which could be a cheap solution to implement in practice (e.g., by using three relays). It even significantly outperforms the *SC-3*-case, whilst its single-commodity counterpart *SC-1* is the most unbalanced and worst performing case.

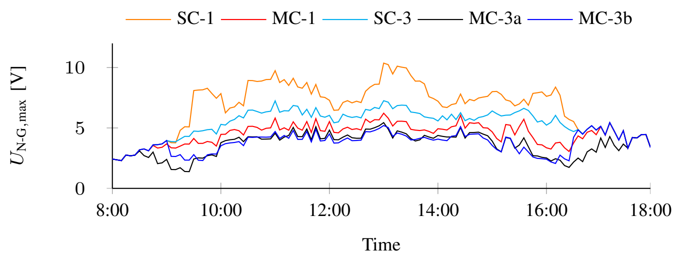

Fig. 3. Maximum neutral point shift per 5-minute intervals.

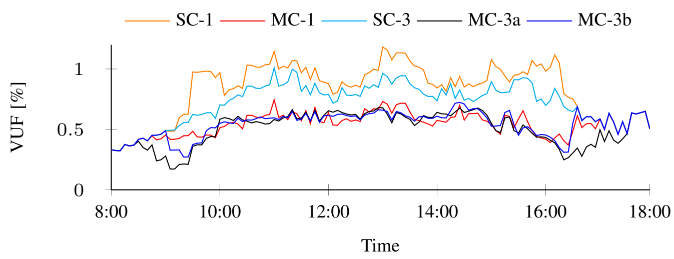

Fig. 4. Maximum VUF as defined in [19], per 5-minute intervals.

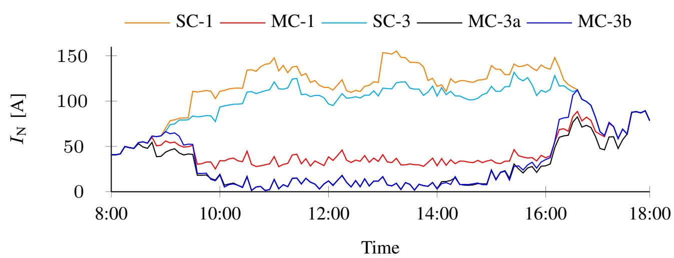

Fig. 5. Maximum current in the neutral conductor at the transformer per 5-minute intervals.

VI. Conclusion

This paper presents a new multi-commodity energy management system that scales linearly in the number of commodities and devices. Application of our approach to phase balancing in the LV grid yields a decrease in losses of up to 41.2% for an unbalanced LV grid with a high penetration of EVs. This shows the added value of multi-commodity support in profile steering for grid balancing and that this may be done without sacrificing performance on the overall power profile. Our findings are consistent with previous research, e.g., of Weckx et al. [14]. Due to the structure of our algorithm, it is easy to incorporate different commodities and devices. Moreover, the presented changes to profile steering are also applicable to an event-driven variant for operational control as presented in [3].

Future research remains in dealing with prediction errors when predictions of future loads are used. In the context of phase balancing, the inclusion of reactive power is left for future work as well. Finally, the development of further specific device level optimization algorithms such as [15], which are efficient and compatible with our method, is needed to incorporate different devices into our approach. This especially holds for devices that are involved with multiple commodities.

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References

[1] G. Hoogsteen, A. Molderink, J. L. Hurink, G. J. M. Smit, F. Schuring, and B. Kootstra, "Impact of peak electricity demand in distribution grids: a stress test," in *PowerTech, 2015 IEEE Eindhoven*, June 2015, 6 pages.

[2] M. E. T. Gerards, H. A. Toersche, G. Hoogsteen, T. van der Klauw, J. L. Hurink, and G. J. M. Smit, "Demand side management using profile steering," in *PowerTech, 2015 IEEE Eindhoven*, June 2015, 6 pages.

[3] G. Hoogsteen, A. Molderink, J. L. Hurink, and G. J. M. Smit, "Asynchronous event driven distributed energy management using profile steering," in *PowerTech, 2017 IEEE Manchester*, June 2017, 6 pages.

[4] H. A. Toersche, "Effective and efficient coordination of flexibility in smart grids," Ph.D. dissertation, University of Twente, October 2016, ISBN 978-90-365-4197-8.

[5] B. Rezaie and M. A. Rosen, "District heating and cooling: Review of technology and potential enhancements ," *Applied Energy*, vol. 93, pp. 2–10, 2012.

[6] A. Molderink, V. Bakker, M. G. C. Bosman, J. L. Hurink, and G. J. M. Smit, "Management and control of domestic smart grid technology," *IEEE Transactions on Smart Grid*, vol. 1, no. 2, pp. 109–119, Sept 2010.

[7] P. Booij, V. Kamphuis, O. van Pruissen, and C. Warmer, "Multi-agent control for integrated heat and electricity management in residential districts," in *4th International Workshop on Agent Technologies for Energy Systems (ATES), a workshop of the 12th International Conference on Autonomous Agents and Multiagent Systems (AAMAS), Minnesota*, 2013, 7 pages.

[8] K. Kok, "The PowerMatcher: smart coordination for the smart electricity grid," Ph.D. dissertation, Vrije Universiteit Amsterdam, July 2013, ISBN 978-90-5986-427-6.

[9] I. Rossi, L. Banta, A. Cuneo, M. L. Ferrari, A. N. Traverso, and A. Traverso, "Real-time management solutions for a smart polygeneration microgrid ," *Energy Conversion and Management*, vol. 112, pp. 11–20, 2016.

[10] S. Weckx, C. Gonzalez, and J. Driesen, "Combined central and local active and reactive power control of PV inverters," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 3, pp. 776–784, July 2014.

[11] W. M. Siti, A. Jimoh, and D. Nicolae, "Distribution network phase load balancing as a combinatorial optimization problem using fuzzy logic and Newton-Raphson ," *Electric Power Systems Research*, vol. 81, no. 5, pp. 1079–1087, 2011.

[12] F. Shahnia, P. J. Wolfs, and A. Ghosh, "Voltage unbalance reduction in low voltage feeders by dynamic switching of residential customers among three phases," *IEEE Transactions on Smart Grid*, vol. 5, no. 3, pp. 1318–1327, May 2014.

[13] G. Hoogsteen, A. Molderink, J. L. Hurink, and G. J. M. Smit, "Managing energy in time and space in smart grids using TRIANA," in *IEEE PES Innovative Smart Grid Technologies Europe, Istanbul*, October 2014, 6 pages.

[14] S. Weckx and J. Driesen, "Load balancing with EV chargers and PV inverters in unbalanced distribution grids," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 2, pp. 635–643, April 2015.

[15] T. van der Klauw, M. E. T. Gerards, G. J. M. Smit, and J. L. Hurink, "Optimal scheduling of electrical vehicle charging under two types of steering signals," in *IEEE PES Innovative Smart Grid Technologies Conference Europe, Istanbul*, October 2014, 6 pages.

[16] T. van der Klauw, M. E. T. Gerards, and J. L. Hurink, "Resource allocation problems in decentralized energy management," *OR Spectrum*, vol. 39, no. 3, pp. 749–773, 2017.

[17] G. Hoogsteen, A. Molderink, J. L. Hurink, G. J. M. Smit, F. Schuring, and B. Kootstra, "Charging electric vehicles, baking pizzas and melting a fuse in Lochem," in *24th International Conference and Exhibition on Electricity Distribution (CIRED 2017)*, June 2017.

[18] G. Hoogsteen, A. Molderink, J. L. Hurink, and G. J. M. Smit, "Generation of flexible domestic load profiles to evaluate demand side management approaches," in *2016 IEEE International Energy Conference (ENERGYCON)*, April 2016, 6 pages.

[19] NEN-EN 50160:2010, "Voltage characteristics of electricity supplied by public distribution networks," 2010.