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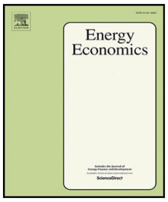

Local energy management: A base model for the optimization of virtual economic units

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ABSTRACT

As non-renewable resources are limited and the overall CO2 emissions need to be reduced drastically, there is an increasing need in making the energy supply more sustainable. This leads to a needed change in the traditional energy system, in which decentralized local energy resources must be better integrated. In order to face the challenges for a future energy management, the consideration of the domestic level is gaining more attention. In this paper, we aim to get insights into the potential value of local cooperations and focus on economic and control issues as to whether and how the domestic level can participate in upcoming solutions. We introduce a possible setup for a virtual economic unit representing a hybrid cooperation of domestic energy participants, whereby the objective of this cooperation is to realize the maximum possible savings for the community with specified individual contracts between the participants and assuming that participants continue to have additional contracts with their energy service provider. We propose a deterministic linear optimization model for determining optimal energy load profiles of the participants with the external suppliers and energy exchange between participants in a virtual economic unit. To efficiently solve this model and get an exact assignment of supply and demand, we present a maximum saving flow algorithm taking into account the underlying bipartite structure of this problem. The solution achieved is specified as a peer-to-peer allocation between the participants involved and provides insights into the aspects that determine the concrete assignment. It also has the advantage of leading to a robust solution within the collaboration case studies for a basic set-up demonstrate the impact of this approach on the economic potential of aggregating local generation and demand at the same time.

1. Introduction

Our energy system is challenged by the limited availability of non-renewable resources and the need for more sustainable power generation to face the greenhouse effect. As a consequence, a fundamental change of this system takes place to a system based to a large extent on renewable energy sources, known under the term 'energy transition'. However, the integration of renewable resources is complex, as these resources are volatile and have a stochastic nature (Kumar et al., 2019). They are to a large extent not controllable, and are to some extent synchronized by the availability of sun or wind leading to large peaks in the generation of electricity. Furthermore, a substantial part of this renewable generation now gets integrated on the distribution grid level. As a consequence, more stress is put on this part of the grid due to temporary peaks, which overburden the possible technical capacities of the actual infrastructure, and by that hinder the further integration of decentralized sustainable energy generation. This leads to a higher demand for flexibility and asks already on distribution grid level for a better coordination between supply and demand. With the current grid hierarchy, the possible influence of local energy optimization and the role of local grid actors on the distribution grid level is still neglected. The steadily ongoing progress of energy transition will change this and is therefore already subject to several projects in progress and funded by international institutions (see Fig. 1 for a sketch of local grid actors and their possible connections).

In this paper we focus on this domestic scope of the common grid infrastructure which offers a growing amount of potential distributed generation (DG) but also distributed storage (DS) and additionally potential load management solutions such as Demand Side Management (DSM) or Demand Response (DR). These assets and approaches form the base to coordinate energy demand and generation as much as possible already locally within the distribution grid. However, for a reasonable adaptation of these opportunities and the provision of corresponding solutions still a lot of issues have to be solved (see e.g. Friedman, 2002;

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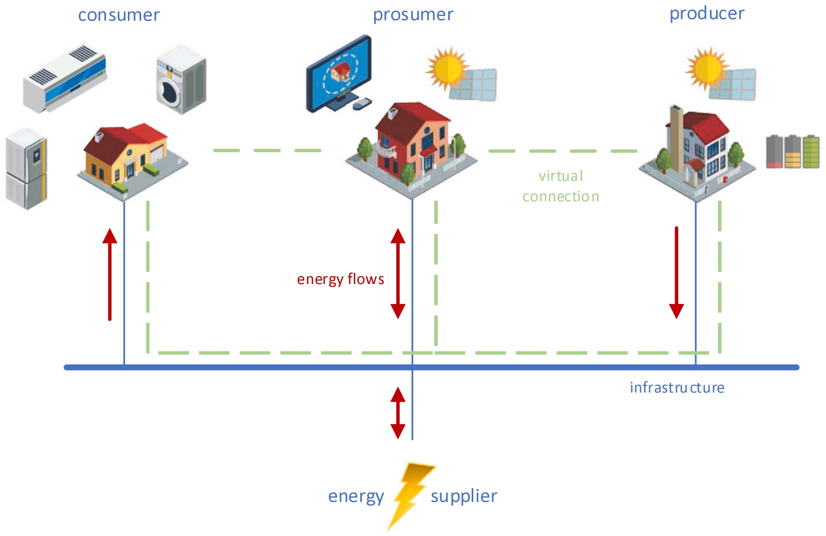

Fig. 1. Domestic energy distribution with virtual connections.

Lopes et al., 2007; Eid et al., 2016) and a growing digitalization of the existing grid infrastructure has to take place (see Colak et al., 2016). Beside technical issues, it is inevitably to create an economic setting in which local actors have a more active involvement. They need to get sensibilized for the local grid congestion issue with new opportunities and possible incentives to support the local balancing of supply and demand. Actual research and policy proposals (like EU Directives) on local energy markets (LEM) and energy communities (EC) underline that. A local perspective must therefore enable the involved parties deriving an economic benefit from the energy trading that is possible due to the bidirectional energy flow and virtual connectivity between them. The fact that these heterogeneous individuals will to a large extent pursue their individual and more selfish objectives, leads to the obvious choice to consider competitive LEM in the first place (see e.g. Parag and Sovacool, 2016). To get insights in this local aspects, we consider a setting, where we allow households to cooperate and interact within their local grid infrastructure. As a further development to familiar approaches of EC, we want to focus on the exact trading of energy flows between the individual participants, and setup this internal energy exchange in addition to an existing contract with an external energy service provider (ESP). Hereby, only the conditions of the individual participants with their ESP are comparative parameter relevant for decision-making. However, for internal purposes, the underlying exact allocation of the internal energy exchange in the achieved solution has to be accessible for the cooperation. The approach may fit for several current discussed projects like the one described in Zhang et al. (2017).

In the next section, we first explain our main idea for virtual economic units (VEU), hereby defining our specific problem setting and explaining the differences to current research. Next, we present a solution approach for a basic VEU in the distribution grid, which can be used to achieve structural insights and possible inputs for future, more complex settings. Where in future work possibilities for a modular extension can be considered, this paper offers a first basic approach for such local energy communities. This solution approach is based on a linear optimization model, being a modified min cost flow model. We then describe an alternative solution algorithm, to achieve more insight in the internal coordination process. Finally, we validate our solution approaches by presenting some case studies. The results show the potential of our approach and the issues at stake, which are explained in the final discussion section.

2. Literature review and environmental basics

In current literature local energy management is an very extensive topic. The research initially attempted to integrate existing and future DG in such a way that the behavior and impact of large conventional power plants is simulated. The economic concept is called commercial virtual power plants (see also Saboori et al., 2011) and aggregates the energy profiles of different DG to participate in local markets or preferably larger energy markets. It is therefore a kind of supply cooperation, and the revenue generated depends on the sales revenue of the aggregated amount of energy. The downside of this environment is, that internal aspects between participants are not considered, if the demand side is present at all. This is a valid concept for large solar or wind parks with access to higher grid levels, but not for local actors on the distribution grid level considered here.

Since then, local energy management is more focused on the increased participation of active consumers and prosumers (as in Sajn, 2016). The basic principle here is to have heterogeneous residents in a particular section of the domestic low-voltage distribution grid trade local energy through virtual peer-to-peer (P2P) connections.[1] Ideas to open up access to wholesale markets for them are only being pursued sporadically due to the barriers to market entry there (like in Zepter et al., 2019. The analysis of concepts for local energy markets or P2P markets on the other hand, has become a popular and very broad field of research (see e.g. Mengelkamp et al., 2017; Sousa et al., 2019; Teotia and Bhakar, 2016). Within this extensive field of research different focus areas can be identified like e.g. McKenna et al. (2018) for multi-objective small community solutions or blockchain-based market designs like e.g. Andoni et al. (2019), Mengelkamp et al. (2018). In general, these competitive solution approaches aim for trading opportunities for local grid actors and for market optimization to enhance local energy trade (see Le Cadre et al., 2020, Etukudor et al., 2020). These approaches in general support individual goals of local actors and do not consider the best possible total result for entire groups of participants. Furthermore, they do not consider the limits imposed by the underlying physical infrastructure (grid) and do not aim for a better distribution of the energy flows in the grid; i.e. do not support to keep energy as much as possible local.

Cooperative concepts and environments, as our approach also envisages, are widely considered to be an EC (see e.g. Azarova et al., 2019, Chronis et al., 2021). A similarity here is the use of a central entity that rationally decides on the energy flows with the objective of maximizing the earnings/savings of the entire community. For this,

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[1] The concrete underlying physical infrastructure may also be given for such type of connection, but in principle it is not required for the presented base approach.

the relationship between the participants denies individual negotiations (active trade). The outcome is a set of preferred interactions between individual participants for the entire community, meaningly that no constellation can achieve better results for the whole entity. However, for realizing such cooperative aspects, participants may not only be interested in purely economical aspects but also social aspects play a role (see e.g. Reijnders et al., 2022).

Our approach will follow such principles and acceptance aspects. Furthermore it will highlight the advantage of knowing the precise allocation determined by a central entity over alternative market solutions. Transparency strengthens internal acceptance, and knowledge about the structure of the underlying energy exchanges in the achieved solution provides the participants involved with information on how changing local behavior can affect the achieved solution. This can help the participants to adapt their behavior to achieve better/more sustainable solutions. By this, the presented concept differs from anonymous trading on local energy markets. EC are increasingly being discussed in connection with research on 'transactive grids', which recently aims a more comprehensive view on the integration of local energy management in active distribution grids or power grids in general (see also e.g. Abrishambaf et al., 2019, Adeyemi et al., 2020). What is underestimated in the research for EC is the explicit consideration of ESP as a basic energy provider or basic contract partner. This basic offer for energy services is currently the main task of this sector and, despite the risk, it is a very lucrative line of business. If consumers/prosumers will be able to conclude several contracts to handle their needed energy services, there will still have to be some form of basic provider for energy services. The political aim is also not to replace the business model of ESP, but to give consumers/prosumers more possibilities to become active (as EU directives show). Yet not all individuals may be able or willing to become active in a LEM or a EC. Our approach focuses on this basic contract with the ESP and also determines the internal energy exchange within the community that leads to the resulting supply and demand that is not used/covered locally and handled by the ESP. An alternative scenario to this would be if the role of the central entity in a community can also act as a trading partner to external parties. The increased level of market influence in a LEM or stronger negotiation power to discuss terms for a joint contract with a ESP simply by pooling participants is the base idea discussed in Aggregator approaches (see e.g. Carreiro et al., 2017; Iria et al., 2018). This extension should be possible for our proposed approach, but in this paper we focus on the comparison to a realistic basic provider in the first place.

The resulting structure has also a slight similarity to research on micro energy markets (MEM), where the integrity of the internal market is inevitably necessary for the self-sufficient aspect of a microgrid (see e.g. Azarova et al., 2019; McKenna, 2018; Moroni et al., 2019). As long as interfaces to other microgrids or the entire distribution grid are available, research on microgrids in general offers interesting possibilities. Note that in a microgrid-based community, a basic supply by an ESP is not mandatory or negotiated by the community, as these concepts provide for self-sufficient control and own energy services. For local energy concepts, however, the use of existing infrastructure will still have priority due to the investment costs incurred for microgrids. To realize the envisioned VEU setting in the existing infrastructure, some basic needs have to be fulfilled that are discussed a.o. under the term 'Smart Grid' (see e.g. Colak et al., 2016). Smart solutions allow for flexible control approaches within the grid infrastructure to ensure the required stability, as well as other metering points besides the smart meter at home (Zhou and Brown, 2017) that can act as possible control points for incentive metering. This enhancement in the structure forms the base for required new tariff structures and control approaches, as we will be able to determine the composition of the energy load values on a smart meter of a user.

3. Basic optimization problem and mathematical formulation

In this section, we present the basic model for the optimization of a basic VEU environment. Given is a set, N, of associated participants of the VEU, which are all in the same local part of the distribution grid (e.g., behind a common transformer). The core objective of the VEU is to support the local consumption of energy generated within the VEU, which supports a better integration of locally generated energy and avoids grid congestion. The model assumes a planning horizon which is discretized into T periods, where every period $t \in \mathcal{T} := \{1,\dots,T\}$ represents a time interval of $time$ minutes. In each period, participants have a given individual demand or supply of energy. Note that these values are the essential parameters of our problem. They are in general not known exactly during the planning phase, and therefore predictions have to be used for these values. Note, that there are many possible approaches to obtain such predictions (see e.g., Hahn et al., 2009; Keles et al., 2016; Ghelardoni et al., 2013), however, these predictions are beyond the scope of this research. We denote the predicted load of participant $n \in N$ for time period $t \in \mathcal{T}$ by $pl_{n,t} \in \mathbb{R}$, where negative values represent energy demand, and positive values energy supply.[2]

In the initial situation, each participant n trades its energy load $pl_{n,t}$ with an external ESP based on the conditions of its individual service contract. This contract specifies the individual tariff conditions for the purchase or sale of energy. We assume different prices for purchase and sale (common practice in most countries), and we also consider prices per unit which may depend on the amount of energy (which is assumed to be common practice in the future). Finally, the individual contracts of the participants may differ from each other and may also depend on the time period. Formally, for participant $n \in N$ and time interval $t \in \mathcal{T}$ these tariffs are defined as follows:

$$v_{n,t}(pl_{n,t}) = \begin{cases} sr_{n,t}(pl_{n,t}) \cdot pl_{n,t}, & \text{if } pl_{n,t} \geq 0 \\ dr_{n,t}(pl_{n,t}) \cdot pl_{n,t}, & \text{if } pl_{n,t} < 0 \end{cases} . \tag{1}$$

Hereby a distinction is made between the individual supply rate $sr_{n,t}(pl_{n,t})$ and demand rate $dr_{n,t}(pl_{n,t})$. These rates depend on the amount of supplied or demanded energy $pl_{n,t}$ and, in general, the supply rate is smaller than the corresponding demand rate, i.e. $sr_{n,t}(x) < dr_{n,t}(y)$ for all $x > 0$ and $y \leq 0$. Based on the given loads of the participants, the initial balance of the VEU for the whole planning horizon can be calculated by summing up all values of $v_{n,t}(pl_{n,t})$ over all time periods and participants.

The aim of the cooperation now is to improve this initial balance by coordinating P2P trades between the supplier subset $s \in S_t \subset N$ and consumer subset $d \in D_t \subset N$ in a period t. To achieve the best possible balance value in this constellation and to reach the optimal system state (i.e. a maximum cost reduction or increased earnings for the overall VEU), a coordination of trades is necessary. We call this the *Energy load adjustment* (ELA) mechanism, which decides how much energy is exchanged between the participants. We denote these amounts by $bal_{t,s,d}$ and they form the decision variables of the ELA. As mentioned, we only allow energy flows between the supplying and the demanding side, but not within the same group. As a result, we get a set $B_t = (S_t, D_t)$ of all possible pairs where energy may flow in a period t. At the end, if we sum up all inflows or outflows of a participant $n \in N$ in period t and offset them with the predicted load value $pl_{n,t}$, we get the optimized load $ol_{n,t}$ of participant n in period t. More formally, we have:

$$ol_{n,t} = pl_{n,t} - \sum_{(n,d)\in B_t} bal_{t,n,d} + \sum_{(s,n)\in B_t} bal_{t,s,n} \quad \forall\, n \in N, t \in \mathcal{T}. \tag{2}$$

Note, that dependent on whether n is a supplier or consumer in period t, one of the two sums will be zero. As these optimized loads $ol_{n,t}$

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[2] Note, that the personal energy demand of a participant is always served first when local energy generation is present, implying that no participant can have supply and demand at the same time.

are the loads which get purchased from/sold to the external provider, the objective function for the ELA mechanism results by replacing the predicted energy load values with the optimized ones. If we then maximize the sum of these computed values, we get the optimized balance value of the VEU for the given planning horizon:

$$\max Z = \sum_{n\in N}\sum_{t\in \mathcal{T}} v_{n,t}(ol_{n,t}). \tag{3}$$

As mentioned, we do not allow arbitrary ELAs between supplier and consumer but restrict these flows in such a way that during a given period no participant changes its role (i.e. you can only sell your surplus of energy or buy your deficit of energy from other participants of the VEU). This can be considered as a reasonable restriction as otherwise the participant with the best conditions could purchase the whole energy demand of the VEU by its external ESP and distribute it via the ELA mechanism. We can integrate this constraint by adding inequalities, which are modifications of an open transportation problem (Bazaraa, 2013):

$$\sum_{d\in D_t} bal_{t,s,d} \le pl_{s,t} \;\; \forall\; s \in S_t, t \in \mathcal{T} \tag{4}$$

$$\sum_{s\in S_t} bal_{t,s,d} \le -pl_{d,t} \;\; \forall\; d \in D_t, t \in \mathcal{T}. \tag{5}$$

The resulting model allows every participant to have various connections to other participants to satisfy or to provide demanded energy load in the VEU, depending on their associated role in a given period. Note, that dependent on the given situation the presented model can easily be extended to incorporate other technical or economical constraints.

In addition, the achieved coordination of energy trades will not affect the overall amount of energy load of the VEU in each time period but reduces the amount of energy load the individual participants exchange with their external ESP. As such, implementing the solution of this problem for a given time period does not directly support keeping energy local. However, having an integrated look at the optimization problems of different time periods may give a participant insight how cost savings may be achieved by moving loads or demands between time periods. To allow this, it is crucial to have good structural insights into the solutions for the basic ELA mechanism.

Since the introduced model introduces no correlation between the different periods, it is possible to solve each period individually. Furthermore, due to the resulting bipartite structure in each period t, there are interesting properties in this structure that we consider in more detail in the next section.

4. Max saving flow algorithm

In the model for a basic VEU introduced in the previous section, we can solve each of the periods separately. The resulting problem for each period can be categorized as a modified min cost flow problem (see e.g., Bazaraa, 2013), with restrictions as given for transportation problems but with a specific objective function. In the case that the objective function is linear, this structure allows us to develop a very efficient algorithm, which also gives a solution fulfilling some other important properties. Therefore (from now on) we consider $dr_{n,t} \mid n \in D_t$ and $sr_{n,t} \mid n \in S_t$ to be independent of the energy amount $pl_{n,t}$, i.e. they are constant for time period t.

Note that now the problem under consideration is, at its core, a simple two-sided market for which basic mechanisms such as auctions can be used to determine the market clearing price and the corresponding market volume for the given period. However, this does not specify settled direct trades between suppliers and consumers, but only trades between the participants and the market, which means that no concrete peer-to-peer trades are determined. This may not directly be a problem, but it leads to several disadvantages. On the one hand, due to the smaller number of players in such local environments and therefore limited market liquidity, the use of a market clearing price can be quite sensitive, as this price can react strongly to minor changes in the given load values. Therefore, such changes can imply a swap of the market clearing price from the cost parameter of one participant to that of another participant. This is considered a drawback, because it gives individual participants or small group of participants some possibilities to influence the market clearing price. In the setting proposed in this paper, we also have the possibility to use clearing prices but based on a concrete assignment, which are thereby not influenced by cost changes of other participants. Hereby, these clearing prices are individual determined values for each assignment and not just one overall clearing price for the whole market. Another drawback of the local market setting is that the difference between purchase and sales prices may be quite large and by that the market clearing prices are much higher in the case of demand overshoot than in the case of supply overshoot. This can be seen as an undesirable discontinuity in the market setup of a local VEU.

As indicated earlier, to overcome the disadvantages of a direct two-sided market approach and to achieve the same maximum reduction in costs or increase in revenue of VEUs, our approach proposes a market mechanism that also specifies a precise allocation of trades between suppliers and demanders (which is not required in the aforementioned auctions). In doing so, this allocation is chosen to allow for a wider range of internal pricing mechanisms within the VEU, including mechanisms that are less sensitive to changes in individual supply and demand values and individual prices. In particular, if a VEU decides not to allocate revenue via the market clearing price but via a fixed allocation of shares in the settled trades (possibly even including a share for the VEU), the exact allocation is mandatory. In summary, the advantage of the proposed allocation over a distribution by a market clearing price is that it determines a specific allocation of trades from the set of all possible allocations leading to the maximum savings of the VEU. This effect allows a broader spectrum of internal mechanisms of settling the payments and earnings, which are more robust against distribution-related manipulations.

In the following we first consider the optimization problem of a VEU for a single period and formulate it as a modified minimum cost flow. For a given period t let $G_t = (N_t, E_t)$ be a bipartite network with node set N_t representing the participants of the VEU. As mentioned in Section Section 3, the participants can be divided depending on their role as supplier or consumer in period t; i.e. we have $N_t = (S_t, D_t)$. Furthermore, for each node the corresponding supply or demand is specified which limits the total possible energy flow on edges out or into a node. The edge set E_t in turn represents potential energy trades between possible pairs of suppliers and consumers implying that $E_t = \{(s,d) | s \in S_t, d \in D_t\}$. With every edge $(s,d) \in E_t$ an individual saving rate $w_{s,d,t}$ is associated, which reflects the advantage of an energy flow of one unit between s and d in t; i.e., how advantageous it is to trade energy via this connection for the given time period t. This rate depends on the difference between the demand and supply rates of the associated participants (nodes) and is given by $w_{s,d,t} = dr_{d,t} - sr_{s,t}$. As we look at each period individually, the resulting structure for every saving rate matrix $w_{s,d,t}$ is that of a transportation problem for which a maximal overall saving has to be determined.

The specific bipartite structure of the above problem incorporates a useful property. More precisely, a saving rate matrix $w \in \mathbb{R}^{a\times b}$ is a Monge matrix, if it fulfills the following Monge property (see e.g. Burkard, 2007):

$$w_{sd} + w_{s'd'} \le w_{sd'} + w_{s'd},\;\; 1 \le s < s' \le a\;;\;\; 1 \le d < d' \le b \tag{6}$$

If we sort the supplier nodes $s \in S_t$ in ascending and the consumer nodes $d \in D_t$ in descending order of their associated tariff parameter $sr_{s,t}$ or $dr_{d,t}$, it is easy to verify that this sorting procedure leads to a saving rate matrix w that fulfills the Monge property. It is known that some problems become particularly easy for Monge matrices, like the already mentioned transportation (network flow) problems, as they

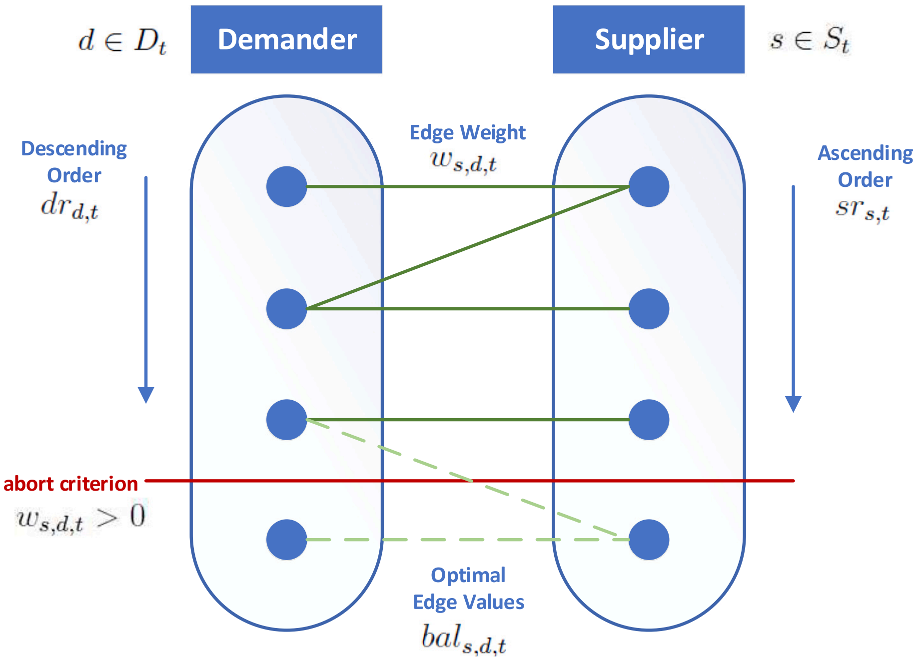

Fig. 2. Maximum saving flow algorithm.

Table 1
Example of a sorted weight matrix.

$w_{s,d}$	d1	d2	d3	d4	d5
s1	20	19	18	17	16
s2	19	18	17	16	15
s3	18	17	16	15	14

can now be solved by a simple greedy procedure. For our specific problem the optimal solution can be computed in $O(n + m)$ time, similar to the *North-West Corner Rule* in a transportation problem (see e.g. Burkard, 2007). Before we discuss the resulting algorithm in detail, we show the sorting procedure with a small example. For this, the following associated and sorted tariffs $dr_{d,t} = \{(30, 29, 28, 27, 26)\}$ for the demanding side and $sr_{s,t} = \{(10, 11, 12)\}$ for the supplying side are given. The corresponding saving matrix $w_{s,d,t}$ is presented in Table 1. Note, that the resulting matrix is sorted lexicographically.

To solve our problem, we can now take advantage of the Monge properties and the structure of the pre-sorted saving rate matrix $w_{s,d,t}$. In an iterative approach we select the most profitable edge $(s, d) \in E_t$ which is always the node pair in the north-west corner of the saving rate matrix $w_{s,d,t}$. As long as the saving value of this possible connection is positive ($w_{s,d,t} > 0$), we establish this edge. Otherwise, we can terminate the algorithm since also all other node combinations cannot yield a positive saving hereinafter. For the established edge, we determine the maximum possible energy flow value $bal_{s,d,t}$ of this edge, which is given by $min(pl_{s,t}, pl_{d,t})$ and assign this flow to the edge. Additionally, we update the remaining available energy supply/demand of the two involved nodes s and d. Note, that this implies that at least one of the nodes will get saturated, meaning that its pl-value gets 0 and that the corresponding row or column in the saving rate matrix $w_{s,d,t}$ can be deleted. Therefore, in the next iteration again, the edge $(s, d) \in E_t$ in the north-west corner of the saving rate matrix w is the most profitable to establish. The Monge property ensures that in this way we get the optimal solution for the considered period, i.e. the optimal values for the decision variables $bal_{s,d,t}$. It is worth mentioning, that this procedure does not lead to crossed edges between the two sets (see Fig. 2 for a visualization of the algorithm based on the underlying graph structure). Furthermore, it is not necessary to compute the whole saving rate matrix for the algorithm, because the sorting procedure ensures we need to consider only the value of the current north-west corner.

The Monge property and the possibility to use the North-West Corner Rule lead to another positive side effect, besides the fact that in each step the trade with the remaining maximum saving is settled. Moreover, market participants have no incentive to choose other, still possible trading opportunities as long as the market rules for determining the distribution of savings among the participants involved in a trade are monotonically increasing in the total savings for both participants. Note, that this is the case when both participants get a specified percentage of the savings, but also the case when a market clearing prize is used. Furthermore, note that in case the participants get a specified percentage of the savings, the resulting solution is a stable solution in two aspects: on the one hand, no pair of participants exists which by a bilateral agreement have an incentive to change their trading scheme (not both can get of better), and on the other hand, a small change in the supply or demand values of individual participants cannot lead to larger changes in the payment schemes. This robustness is an important property for such local market schemes, or particularly for cooperations, and is not given when an auction-based scheme is used.

5. Case studies

In the previous sections we presented a basic model for a VEU and an efficient corresponding algorithm to determine the optimal energy flows within the VEU. In this section the aim is to evaluate this VEU concept for realistic scenarios, so that we can analyze how much local energy trading is possible, how and which parameters influence the market volumes and to what extent the VEU can benefit from the local trade. To achieve this goal, we determine the operational outcome of a VEU in different seasonal scenarios (one scenario for each of the four seasons) and in scenarios which differ in the composition of the local market. For our case studies we generate a heterogeneous composed VEU that consists of 100 participants. All of them are connected to the same local part of the distribution grid and have a contract to purchase their energy consumption or to sell their energy production via an external ESP.

In order to work with realistic scenarios, we create energy load profiles for the participants by a profile generator, based on studies

Table 2
Seasonal results.

	Spring	Summer	Autumn	Winter
Origin Balance	−1.320,70 €	−354,93 €	−1.519,96 €	−2.216,73 €
Optimized Balance	−1.044,68 €	−0,95 €	−1.346,80 €	−2.134,40 €
Savings	276,02 €	353,97 €	173,16 €	82,33 €
Demand Quantity	8442 kWh	8364 kWh	8420 kWh	8434 kWh
Supply Quantity	7514 kWh	14617 kWh	6464 kWh	1480 kWh
ELA Energy	1442 kWh	1836 kWh	895 kWh	431 kWh
Energy Sale	4378 kWh	10610 kWh	4325 kWh	288 kWh
Energy Purchase	5307 kWh	4357 kWh	6281 kWh	7242 kWh

from Hoogsteen et al. (2016). To get a good diversification of the household structure, we use all provided profile types which the generator offers (they differ in household size and the work status of the residents). For each scenario we create energy profiles for 3 days subdivided in intervals of $time = 15$ min resulting in 288 time periods. For the local generation of energy we only consider PV panels. In our basic setup, only 50% of the participants are equipped with this supply option. To examine the influence of the market composition, in a second step, we vary this fraction of suppliers within the VEU to 25% and 75% for two of the seasonal scenarios. In the base scenario storage options are not included at all. Finally, the climate data used is based on the Berlin area.[3]

For the economic part we use individual linear tariff structures for each participant, which are based on a triangular distribution. We want to achieve not only similar price levels for all participants in the planning horizon, but also a realistic price diversity between the individual participants. The mean value for this distributions is based on the average purchase tariff, respectively the average sale tariff in Germany[4] with a deviation of 20% from these mean values for upper and lower limits. A consequence of this parameterization of the distributions is that the two price intervals are disjoint. This effects the problem instances, in the sense that the tradable amount of energy is not affected and is therefore equal in all cases. As a result, the abort criterion within the algorithm always states that there is no more supply or demand available in the market.

The used algorithms and the data generation are implemented in Python 3.7[5] and CPLEX 12.10 is used to solve the optimization problem.

Table 2 shows the results achieved for the comparison of the four seasons. The table contains the origin balance values of the VEU (without trade) for each seasonal scenario in the first row and the optimized balance values in the second row. The resulting improvements for the VEU balance are given in the third row. At first glance, the balance value of the VEU is significantly better in the summer scenario and the savings of the VEU balance in this season is quite high. This depends mainly on the generated amount of energy (row ‘Supply Quantity’ in Table 2), due to the increasing number of hours of sunshine and the associated trading periods, which effects the amount of energy we can use for local energy load adjustments (row ‘ELA energy’) and the amount that we sell to the ESP (row ‘Energy Sale’). The results in the table indicate that we can use four times more energy for the ELA in the summer compared to the winter. Furthermore, it is interesting that the energy supply in summer is ten times as large as in winter. On the other hand the consumption of the VEU is at a similar level in each season (row ‘Demand Quantity’). This implies that we can use only a fraction of the surplus of solar energy for ELA. The reason for this is that there is not enough demand available during the sunny periods. So, the VEU still has to purchase a large amount of energy from the ESP (see row ‘Energy Purchase’) in other periods. This indicates that for the energy transition it is of importance that next to the amount of energy supply, the distribution of the energy demand of the VEU should also be changed over time. To illustrate this, Fig. 3 shows the external energy flows over the planning horizon for the four seasons, with negative values representing energy demand, and positive values showing energy supply. The graphs indicate that in our model, the market will clear demand or supply and has to handle the residual amount of energy via the ESPs. This also indicates that a focus on only one type of renewable generation (in our case, solar) is not supporting local energy trades.

In Fig. 4, more detailed information on the market composition throughout the day is given. The graphs indicate that the fraction of producers on a specific point in time depends on the weather conditions, PV alignment, the time of day and also the time of year, (i.e. the possible time window for power generation starts earlier and lasts longer in summer, even if weather-related influences cause interruptions, such as on Day 2). The chart also indicates that we only have a few hours with production in winter, with a peak around noon. These findings give more detailed insight how large the focus on one generation source (solar) effects the market volume of internal trades (see also Fig. 5 where these values are given). On sunny days the volume is limited by the quantity of demand, as we can see on Day 1 and 3 in summer. The fraction of producers is comparable in these days and based on the weather the amount of energy supply is quite high. However, the trade peak is at evening times, when the residents are back home and the demand consequently rises. However, in winter, the market volume is limited by the amount of supply because the time window for power generation and therefore market activity is significantly shorter. From this, we can conclude that it is important to identify at which time trade is possible throughout a day and if the market is heavy on demand or supply at a specific time period or season. This analysis can be used to decide on choices for the type and compilation of renewable generation in a VEU but also for choices of appliances used for certain demands (e.g. heating). The latter may lead to more beneficial times or market compositions, especially if we prefer PV as the only renewable energy generation source for a VEU.

Therefore in the following, we analyze different scenarios where we vary the fraction of producers. The corresponding results are presented in Table 3. In the first (and fourth) column we see the initial results in summer (and winter, respectively) where a 50% fraction of the households has PV-generation. The following columns then show the results for scenarios with a 25% and a 75% penetration in the specific season. When we decrease the fraction of households with PV panels to 25% in summer (Column 2), the total amount of energy supply is lower (row ‘Supply Quantity’ in Table 3), but at the same time the amount of internal trading grows by 27% (row ‘ELA energy’) which leads to an increase of the savings value by 23% (row ‘Savings’) in this season. This also explains the achieved results, when we increase the fraction of households with PV panels to 75% (see Column 3). Now, for the very high amount of energy supply only a few customers are present, resulting in a decrease in the amount of ELA energy flows (45%) and reduced savings (44%).

In contrast, in the winter period we can notice a somehow opposite result. When we decrease the proportion of suppliers to 25% (Column 5) we limit the already small supply and consequently cannot see any increase in savings (row ‘Savings’) or the amount traded (row ‘ELA energy’). We therefore may expect that an increase of the fraction to 75% should result in an increase of savings and the amount traded. However here another aspect becomes more dominant — the own consumption of a resident. In winter, the PV output of a participant is smaller compared to the summer and so the overall generation surplus (row ‘Supply Quantity’) is already used to a large extent in own consumption.

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[3] Source Astral 1.4 https://astral.readthedocs.io/en/latest/

[4] Data from the Federal Ministry for Economic Affairs and Energy or the Federal Statistical Office of Germany

[5] http://www.python.org

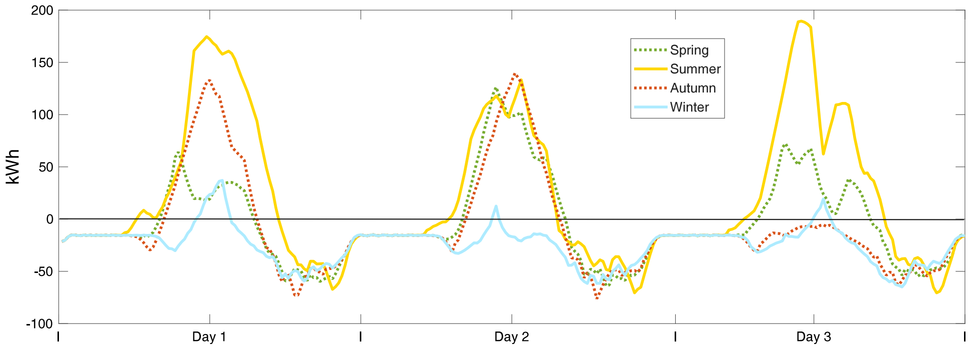

Fig. 3. External energy flows.

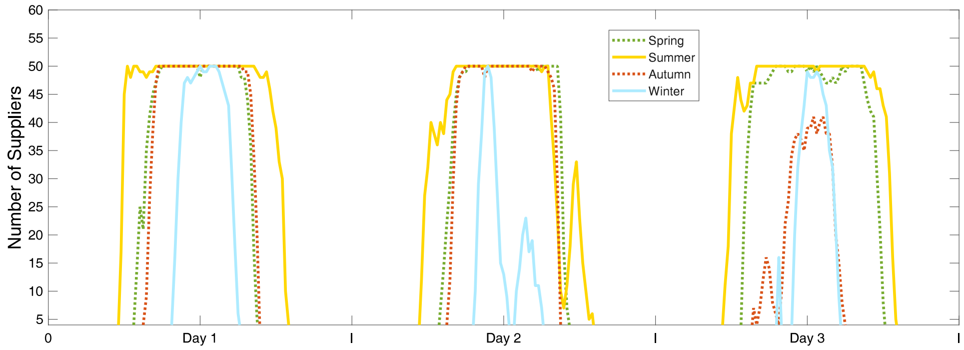

Fig. 4. Virtual market composition.

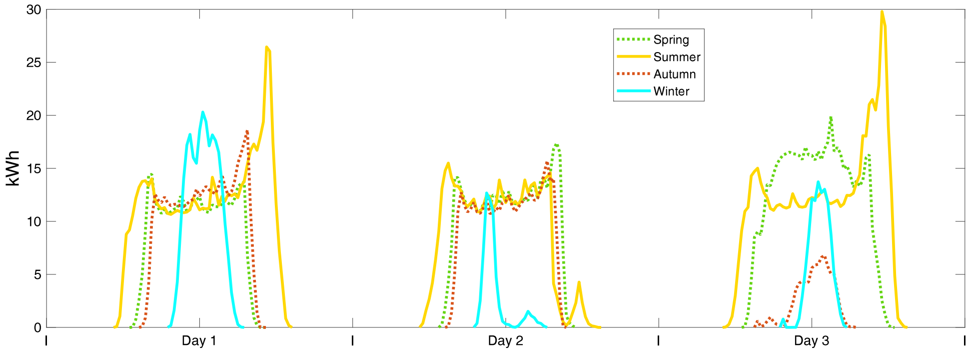

Fig. 5. ELA energy flows.

These presented results have shown that the season, time and the time-dependent composition of a local market have a quite diverse influence on its overall performance and it is not possible to make a general statement about how the market should be structured throughout a year. However, with our tool and the knowledge of the energy flows in the system, we are able to determine a beneficial static or more dynamic structure with flexible participants, who are able to join a VEU temporarily, but stay unattached in the long term.[6] The tool can be the base to support the participants in investment decisions, i.e., to decide if it is beneficial to invest in a PV (or other appliances) and to step into the market as an additional supplier and to determine if this decision is of value to the VEU.

6. Discussion

The case studies show that the considered setting we are able to improve the balance for a basic, but realistic VEU, simply by coordinating local energy supply and demand with the ELA mechanism. Furthermore, we provide the targeted structural insights and additional information for more complex settings, i.e. the influence of the market composition in general and the amount of supply or demand at a certain point in time. The conclusion is that we have to extend the flexibility of a VEU to react better to the market parameters if we want to exploit more of the still huge potential in this setting. In the following we point out possible expansion strategies.

A simple solution to extend the flexibility is to allow participants to join and leave a VEU cooperation dynamically. In this case, the VEU can regulate the market composition by temporarily accepting additional participants who provide the missing supply or demand for additional trading, if the market is heavily one-sided. With our tools, a VEU is able to forecast and prepare for such scenarios. The downside of such dynamic participant affiliation is that it is both technically and legally

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[6] This may turn into other billing or fee concepts with participation levels, but is not a topic of this paper. See also in Cap. 6

Table 3
Variation results.

	Summer 50%	Summer 25%	Summer 75%	Winter 50%	Winter 25%	Winter 75%
Origin Balance	−354,93 €	−1.446,16 €	795,60 €	−2.216,73 €	−2.386,62 €	−2128,99 €
Optimized Balance	−0,95 €	−1.007,34 €	994,87 €	−2.134,40 €	−2.334,59 €	−2.082,69 €
Savings	353,97 €	438,82 €	199,27 €	82,33 €	52,03 €	46,30
Demand Quantity	8364 kWh	8357 kWh	8404 kWh	8434 kWh	8375 kWh	8422 kWh
Supply Quantity	14617 kWh	7243 kWh	22628 kWh	1480 kWh	586 kWh	1837 kWh
ELA Energy	1836 kWh	2275 kWh	1009 kWh	431 kWh	261 kWh	236 kWh
Energy Sale	10610 kWh	3860 kWh	18284 kWh	288 kWh	0 kWh	606 kWh
Energy Purchase	4357 kWh	4974 kWh	4060 kWh	7242 kWh	7789 kWh	7191 kWh

complex to control. When we focus on a static cooperation instead, the most promising solution to boost the flexibility of the VEU is to consider energy load shifting options to exploit more beneficial time periods. This is an already discussed aspect of decentralized energy management, and the energy load shifting options would allow the VEU to shift parts of their energy demand (via demand side management) or energy supply (via storage integration) to get the required flexibility. The downside is that this may results in a conflict of aims, between the use of the ELA mechanism (a periodic decision) or to locally shift the load (leading to a multi-period decision). Our tool and its basic setting, can be used to address this realistic extension. Note, that the load shifting application will also benefit the system, if it is the case that the two price intervals of supply and demand are not disjointed. In that case, we can shift the non-tradable energy load in a certain period to another period, instead of using, the most likely, less beneficial conditions of the ESP.

Another conclusion of our studies for a VEU management is to diversify the sources of power generation within a cooperation and also consider more controllable elements in their energy environment, like microCHPs or heat pumps. In that way, the VEU would gain more control over the times of local energy production and consumption and the way additional energy demands (e.q. heating) can be included in this setting to also benefits a more comprehensive view on energy management. An integrated approach can furthermore benefit the relationship with the net operator — by supporting local net stability. The VEU is already able to create more predictable local energy flows and therefore can be of value for the net operator. Another advantage is the use of rolling planning, especially with controllable energy generators. Using a long-term planning horizon for optimization, but updating it at fixed intervals and renewing it with changed data helps to quickly identify deviations and refine the plan.

To summarize, the developed model and the maximum saving flow algorithm find optimal values for the considered setups and give us valuable insights what is achievable in this simple setup and also possible in more complex setups. These insights could be achieved since we built our base approach from scratch and as simple as possible. Additionally, with our tools we also gain information about the virtual energy flows in this local energy community and the composition of the achieved savings. We may use these insights to develop optimal strategies for internal pricing (profit-distribution) in later stages with game theory approaches, that follow the efficient contract theory. The question in this context is, how to design the contracts for the participants to get a stable cooperation. Finally, external stakeholder, such as net operators, may also use these insights to develop pricing strategies for their network charges.

If the integration of decentralized energy management solutions will be intensified and the overall benefits of these solutions will have an effect on the political decisions, it is also possible to address other questions concerning the VEU setting or local energy markets in general. The allowance of such economic cooperation leads to technical and economical issues next, and also to further detailed questions on issues of law and tax regulation.

CRediT authorship contribution statement

Benjamin Hildebrandt: Conceptualization, Methodology, Software, Visualization, Writing – original draft. **Johann Hurink:** Supervision, Writing – review & editing. **Michael Manitz:** Supervision.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2023.107252.

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