



Multi-vector optimization scheme for distributed components in energy islands

Stepan Gagin · Michael Bettermann · Hermann de Meer

Received: 11 May 2023 / Accepted: 14 June 2023 / Published online: 4 August 2023
© The Author(s) 2023

Abstract Recent advancements in energy systems, such as the emergence of prosumers and sector coupling approaches, introduce additional flexibilities over multiple energy sectors, such as heating, electricity, and mobility. Due to the complexity of such distributed systems, the optimization of energy allocation is a non-trivial task, especially considering constraints and limitations introduced by distributed devices or sub-systems. Additionally, the variety of devices forces approaches to be highly situational and not universally applicable. In this paper, a two-level optimization scheme is proposed, which aims at reducing the optimization complexity of sector-coupled systems. The multi-vector optimization embedded in the two-level optimization scheme is formulated as a mixed-integer linear problem, optimizing the energy flow between domains, which are modeled as an abstraction of a sector. Distributed devices are modeled as components that represent an abstraction of devices connected to an energy domain. The optimization process is evaluated based on the data from a residential complex in Ghent, Belgium. It shows that the approach is capable of minimizing costs, CO₂ emissions, and dependency on external resources.

Keywords Energy optimization · Multi-energy systems · Sector coupling · Energy Management Systems

Multivektor-Optimierungsschema für verteilte Komponenten in Energieinseln

Zusammenfassung Neuste Entwicklungen in Energiesystemen, wie beispielsweise die Etablierung von Prosumern und Sektorkopplungsansätzen, erschließen zusätzliche Flexibilitäten über mehrere Energiesektoren, wie Wärme, Elektrizität oder Mobilität. Aufgrund der Komplexität solcher verteilten Systeme ist die Optimierung der Energie-Allokation keine triviale Aufgabe, insbesondere wenn die Nebenbedingungen und Limitierungen einzelner verteilter Geräte oder Subsysteme miteinbezogen werden. Außerdem erzwingt die hohe Variabilität der Geräte, dass Lösungsansätze nur situationsbedingt und nicht universell angewendet werden können. In diesem Artikel wird ein zweistufiges Optimierungsschema vorgestellt, das die Komplexität von Sektorkopplungsansätzen reduziert. Das Multivektor-Optimierungsproblem, welches eingebettet in das zweistufige Optimierungsschema ist, ist als gemischt-ganzzahliges lineares Programm formuliert und optimiert den Energiefluss zwischen Domänen, die als Abstraktion von Sektoren definiert sind. Die verteilten Geräte sind als Komponenten modelliert, die eine Abstraktion von mit Energiedomänen verbundenen Geräten darstellen. Der Optimierungsprozess wurde basierend auf einem Datensatz eines Wohnkomplexes in Gent (Belgien) evaluiert. Die Evaluation zeigt, dass der präsentierte Ansatz Kosten, CO₂-Emissionen und die Abhängigkeit von externen Energiequellen minimieren kann.

Schlüsselwörter Energieoptimierung · Multi-Energie-Systeme · Sektorkopplung · Energie-Management-Systeme

S. Gagin (✉) · M. Bettermann · H. de Meer
Chair of Computer Networks and Computer
Communication, University of Passau,
Innstraße 43, 94032 Passau, Germany
stepan.gagin@uni-passau.de

1 Introduction

In modern energy systems many consumers become prosumers [8] by installing Photo-Voltaic (PV) panels or electrical storage devices. Additionally, the concept of sector coupling is becoming more prevalent [14]. An Energy Island (EI) is defined as a geographically delimited organization of distributed energy consumers and producers which strive to optimize their cost, CO₂ consumption and the independence from external sources. EIs are complex systems of interconnected load, generation and storage units in various energy sectors, such as electricity, heating and mobility, distributed over multiple buildings. This complexity makes it difficult to optimize the planning of energy generation and consumption over multiple devices in different locations. Each device introduces different location-dependent constraints, e.g., the coefficient of performance of heat pumps, which can be dependent on their environment. In this paper, this issue is defined as multi-vector optimization problem. Due to the heterogeneity of the EI's structure as well as the plethora of possible local constraints of each device, solutions are forced to be highly complex and uniquely suitable for individual sites. Depending on the objective of a community, different preferences might be given to the activation order of generators, such as financial opportunities, CO₂ emission reduction incentives or reducing the dependency on external sources or, in other words, increasing self-sufficiency. However, the realization of such objectives introduces additional complexity, for instance, the variability of energy prices realized by dynamic electricity tariffs and other demand response programs.

This paper introduces an optimization scheme which can be used by a centralized decision maker to optimize energy allocation over multiple energy sectors for a group of energy producers, consumers and prosumers, distributed over multiple buildings. The proposed two-level optimization scheme separates the optimization process into domain-specific optimizations, where local device limitations and domain-specific constraints are enforced, and a multi-vector optimization, which optimizes the energy flow between domains and their respective domain-specific optimizer. Splitting the optimization problem into two smaller problems decreases the complexity of the system, since the multi-vector optimization can neglect constraints of individual devices and provide a consumption schedule for each domain, which is then realised by a domain-specific optimizer. To achieve the simplification of the multi-vector optimization, components are defined, which generalize the behavior of distributed devices or sub-systems by only considering basic functionalities, such as storage systems with only charging and discharging limits and an energy conversion efficiency. This modelling of devices or sub-systems allows the existence of domain-specific optimizer, which can operate under

local constraints and can be established uniquely, depending on the underlying systems needs.

Using the proposed multi-vector optimization method, optimal scheduling of generation and consumption, regarding the minimization of costs, CO₂ emissions and the maximization of self-sufficiency, is achieved, where flexibilities, provided over multiple energy-sectors or domains are exploited. Based on data gathered from a residential site in Ghent (Belgium), it is shown that the multi-vector optimizer provides an optimal consumption schedule for the distributed appliances. The main contributions of this paper are as follows:

- The paper introduces a two-level optimization scheme for scheduling energy generation and consumption located in an EI.
- A generalization model for different types of energy generators and consumers is proposed.
- A case study for the optimization approach is provided, where the system is evaluated on real-world data collected in a residential district in Ghent, Belgium.

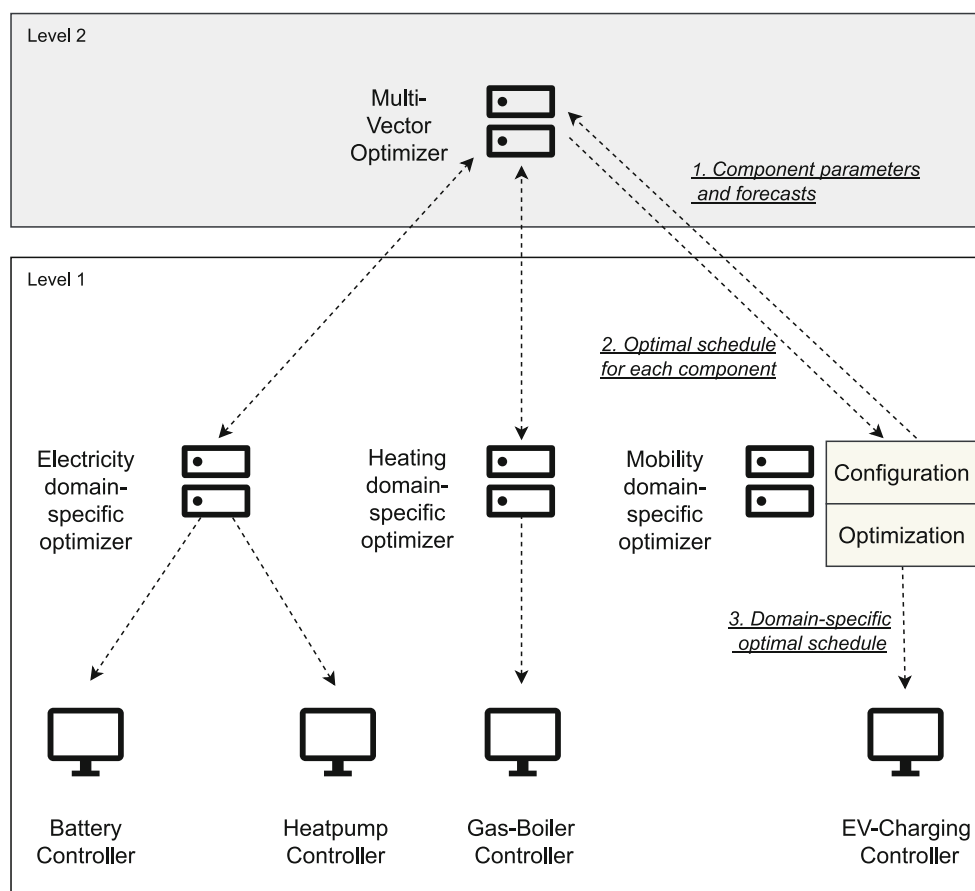
The paper is organized as follows: Sect. 2 presents the related work and compares the methods to the system proposed in this paper. Next, Sect. 3 provides a description of the two-level optimization scheme, followed by Sect. 4, where an outline of the introduced components and objective function for the optimization approach is provided. Sect. 5 defines metrics used to evaluate the results of the multi-vector optimization in a real-world residential area in Ghent and a concise explanation of the system's behaviour is provided. The concluding Sect. 6 is devoted to final remarks and potential future research on this topic.

2 Related Work

Load scheduling [1], integrated with renewable energy generation and storage management [9], is a common functionality of Energy Management System (EMS) [2]. Additionally, newly developed platforms allow control and optimization of not only the electricity sector, but also other energy sectors such as heating, which supports the coupling of sectors [7].

Several approaches for energy optimization and scheduling based on integer programming methods are proposed [12]. Zhai et al. [19] provide a mixed-integer linear programming approach where the operational costs of individual units spanning over the electricity, heating and gas sectors get minimized. However, in contrast to the methodology presented in this paper, only the operational costs get minimized, while additional factors such as CO₂ emissions or self-sufficiency are ignored. Liu et al. [11] provide an in-depth description of Combined Heat and Power (CHP) generation systems and show the flexibility potential for such systems. However, the complexity

Fig. 1 Outline of the two-level optimization scheme of the site in Ghent [4]. Icons are taken from Material Icons (<https://github.com/google/material-design-icons>) available under the Apache License Version 2.0 (<https://www.apache.org/licenses/LICENSE-2.0.txt>)



of CHP might cause scalability issues for optimization schemes if the number of devices rises.

Two-level optimization schemes aim at separating the initial complex problem into multiple smaller optimization problems, by logically splitting the underlying system into two parts. For instance, Rastegar et al. [15] present an approach, where in the first level each household implements a residential energy management system to minimize customers' costs. On the second level, the system operator modifies the households' electrical demand by solving a multi-objective optimization problem. In another approach, the coordination of data center operators and a system operator is implemented as a demand response program, which is split into two levels [10]. In the lower level the data center operators try to buy energy as low as possible from the system operator, while maintaining quality of service requirements, while the system operator tries to maximize the systems profits in the upper layer. The two-level optimization approach proposed in this paper allows splitting the optimization process into two smaller parts, namely a multi-vector optimization and a domain-specific optimization, resulting in a reduction of complexity.

In this paper, devices and sectors are generalized into components and domains, allowing for a more abstract view on devices and sectors, by narrowing them down to their most essential attributes and func-

tionalties. This aspect is not covered by other multi-level optimization models such as the one depicted by Wu et al. [18]. A modeling of battery storage systems and grid connections for the optimization of energy storage and Electric Vehicle (EV) charging session utilization is provided by Danner et al. [3]. However, this method merely allows the modeling of specific flexibility potentials and does so only for the electricity sector. While the approach by Sun et al. [16] introduces a flexible generation model for power balancing for an electricity grid in combination with an appropriate flexible and base-load modeling, it does not consider any interconnections between multiple energy sectors, e.g., between electricity and heating, and only remains in the electricity sector.

3 Two-level Optimization Scheme

All devices and their connections in an EI are represented as components and domains in the proposed optimization approach. Components are abstractions of distributed consumption and generation devices or sub-systems, which are generalized to its most basic functionality, e.g., a storage system which is only modelled with the device's capacity and charging or discharging limits. Each energy domain represents a shared medium where energy can be exchanged between components and, therefore, abstracts the idea

of energy sectors. Components are connected to domains and can consume or generate energy in a domain.

Devices connected to the same domain can have particular domain-specific restrictions. For instance, in the electricity domain the voltage magnitude and frequency have to stay within set ranges. Additionally, individual devices may have restrictions, e.g., regarding the operation time or ramping rate. Moreover, the size of an EI may vary from only one building to a city district with multiple buildings. In order to create a scalable and device-agnostic solution, a two-level optimization scheme is proposed and outlined in Fig. 1.

The first level is dedicated to the domain-specific functionalities and consists of two functional blocks for each domain, as outlined in the mobility domain-specific optimizer in Fig. 1. The domain-specific configuration blocks are responsible for setting up parameters of components connected to the domain, while the domain-specific optimization blocks are in charge of scheduling the specific devices' operations considering domain-specific restrictions. The second level of the scheme is a multi-vector optimizer that manages energy flows between domains. The optimization scheme is defined as follows:

1. Domain-specific configuration functional blocks send the parameters of each component in its domain, such as energy conversion efficiency, energy generation and consumption limits. These parameters are determined according to technical specifications of the devices and outputs of prediction algorithms for energy consumption and generation.
2. The multi-vector optimization located at the second level in Fig. 1 is performed and optimal energy supply and consumption are found for each component.
3. Based on the output of the multi-vector optimization, the domain-specific optimization blocks perform optimization within their domain. Domain-specific optimization might have the same optimization objectives as the multi-vector optimization, however additionally new objectives and constraints can be introduced in order to reflect restrictions and preferences of the specific domain. Ideally, the domain-specific optimizer creates an operation schedule such that its energy profiles aligns with the energy profile from the multi-vector optimizer. Due to the constraints of real devices or forecasting errors the alignment of the multi-vector optimizer energy profile and the domain-specific optimizer energy profile may not be achieved. An energy profile is defined as a sequence of energy consumption or generation values in every time step t over the entire time horizon \mathcal{T} .

It is important to mention that the assignment of devices to particular domain-specific optimizer is similar to the assignment of components to domains in

multi-vector optimization. However, devices corresponding to interconnector components, e.g., heat pumps, can be assigned to any of the two connected domains. Note, interconnectors should be connected to only one domain-specific optimizer, in order to avoid conflicting control signals, which is the reason why the heat pump controller in Fig. 1 is only attributed to the electricity domain-specific optimizer and not the heating domain-specific optimizer.

4 Multi-vector optimization

This paper focuses on the first two steps of the proposed optimization process outlined in Sect. 3, namely the configuration of components and the multi-vector optimization. Due to unavailability of local domain controllers at the residential site in Ghent, Belgium, the domain-specific optimization step mentioned in Sect. 3, is left for future work. Component $c \in \mathcal{C}$ introduces decision variable $S_d^c(t)$ when it generates energy in domain $d \in \mathcal{D}$ and decision variable $D_d^c(t)$ when energy is consumed from domain d at any time step t , where \mathcal{C} denotes the set of all components (see Table 1) and \mathcal{D} represents the set of all domains. It is important to note that all energy-related variables and parameters of components are in the same energy unit. The time horizon \mathcal{T} is modelled as a set of discrete consecutive time steps $\mathcal{T} = \{1, 2, \dots, t_{\max}\}$. Time horizon \mathcal{T} and the duration of each time step t_i are configured for each EI individually, depending on the properties of each component.

The multi-vector optimization is mathematically formulated as mixed-integer programming problem and defined as follows:

$$\text{minimize}_{S_d^c(t), D_d^c(t)} \omega_1 \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}_d} S_d^c(t) \cdot r_c(t) \quad (1)$$

$$+ \omega_2 \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}_d} S_d^c(t) \cdot p_c(t) \quad (2)$$

$$+ \omega_3 \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}_d} S_d^c(t) + D_d^c(t), \quad (3)$$

subject to

$$S_d^c(t) \geq 0, \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{C}, \quad (4)$$

$$D_d^c(t) \geq 0, \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{C}, \quad (5)$$

$$\sum_{c \in \mathcal{C}_d} S_d^c(t) = \sum_{c \in \mathcal{C}_d} D_d^c(t), \quad \forall t \in \mathcal{T}, \forall d \in \mathcal{D}, \quad (6)$$

$$S_d^c(t) = \overline{S}_c(t), D_d^c(t) = 0, \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{A}, \quad (7)$$

$$D_d^c(t) = \overline{D}_c(t), S_d^c(t) = 0, \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{B}, \quad (8)$$

$$S_d^c(t) \in [0, \overline{S}_c(t)], D_d^c(t) = 0, \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{M}, \quad (9)$$

$$D_d^c(t) \in [0, \overline{D}_c(t)], S_d^c(t) = 0, \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{N}, \quad (10)$$

$$\sum_{t=t_x}^{t_y} D_d^c(t) = E_c, \quad t_x, t_y \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{L}, \quad (11)$$

$$D_d^c(t) \in [0, \overline{D}_c(t)], S_d^c(t) = 0, \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{L}, \quad (12)$$

$$E_c(t) = E_c(t-1) + \mu_c(t) \cdot D_d^c(t) - \frac{1}{\mu_c(t)} \cdot S_d^c(t), \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{H}, \quad (13)$$

$$E_d^c(t) \leq C_c, \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{H}, \quad (14)$$

$$S_d^c(t) \in [0, \overline{S}_c(t)], \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{H}, \quad (15)$$

$$D_d^c(t) \in [0, \overline{D}_c(t)], \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{H}, \quad (16)$$

$$S_i^c(t) = \mu_c(t) \cdot D_d^c(t), \quad \forall t \in \mathcal{T}, d, i \in \mathcal{D}, \forall c \in \mathcal{K}, \quad (17)$$

$$S_i^c(t) \in [0, \overline{S}_c(t)], D_i^c(t) = 0, \quad \forall t \in \mathcal{T}, i \in \mathcal{D}, \forall c \in \mathcal{K}, \quad (18)$$

$$D_d^c(t) \in [0, \overline{D}_c(t)], S_d^c(t) = 0, \quad \forall t \in \mathcal{T}, d \in \mathcal{D}, \forall c \in \mathcal{K}, \quad (19)$$

where \mathcal{T} is the set of all time steps, \mathcal{D} is the set of all domains. $E_c(t-1)$ defines the energy in the storage component at the previous time step. Table 1 provides an overview of each component type and their respective notation used in Expressions (1)–(19).

Multiple components can be connected to a single domain. At every time step t energy consumption and generation in each domain has to be balanced which is reflected in the constraint given in Eq. (6).

The Constraints (7)–(19) are introduced by different components. Fixed generation and consumption components cannot be controlled by management of the EI, but the predicted energy consumption $\overline{D}_{\text{fixed}}^d(t)$ or generation $\overline{S}_{\text{fixed}}^d(t)$ is known for each time step, as indicated in Eqs. (7) and (8). Flexible generation and consumption components introduce a limit of energy generation (Constraint (9)) and consumption (Constraint (10)) that they are allowed to contribute to the domain at time step t . These parameters can be calculated as rated maximum power of devices multiplied by a duration of the time step t . A time-shiftable consumption component adds constraint that in a set of consecutive time steps

$\{t_x, \dots, t_y\} \subseteq \mathcal{T}$, where t_x and t_y realize the starting and ending time step of the respective interval. The component consumes E_c energy in total, which is expressed in Eq. (11). The maximum energy that can be consumed in every time step by time-shiftable load component is determined by parameter $\overline{D}_c(t)$, as shown in Constraint (12).

During the charging process of storage components energy is consumed from domain d and stored in the component. In the discharging process the energy is generated in domain d and consumed from storage. The efficiency of the energy conversion is given by parameter $\mu_c(t)$. The energy stored in storage at time step t is given by Eq. (13). The component has a limited capacity of energy storage, as shown in Inequality (14). The initial energy stored in the component before the first time step is given by $E_c(0)$. The maximum energy that can be generated and consumed in domain d is given by the corresponding parameters $\overline{S}_c(t)$ and $\overline{D}_c(t)$ as shown in Constraints (15) and (16).

An interconnector component is connected to two domains d and i and allows the energy transfer from one domain to another. The energy is consumed from domain d and generated in another domain i with energy efficiency of $\mu_c(t)$ as shown in Eq. (17). Similar to other components the maximum energy which can be supplied to the domain i and maximum energy that can be consumed from the domain d are determined by component parameters, as given in Constraints (18) and (19).

The three objectives that EI operators want to achieve are represented in the objective function (Expressions (1)–(3)) formulated in the multi-vector optimization. The objective function is constructed as a weighted sum of three terms corresponding to different objectives. ω_1, ω_2 and ω_3 are the weights that can be adjusted by EI operators to set the priority of the objectives. The first term given in Expression (1) relates to the use of energy sources with the lowest green house gas emissions. For each component that generate energy the CO₂ emission index $r_c(t)$ is assigned for each time step t . The CO₂ emission index values used in the optimization are normalized between 0 and 1.

The second term depicted in Expression (2) is related to the financial cost of energy. For any component the cost of energy $p_c(t)$ can be defined for each time step t . This cost represents the financial cost of supplying a unit of energy by a generation component. Note that negative cost $p_c(t)$ can be assigned to consumer component to reflect the revenue of selling energy to this component. It can be used to model the case of energy injection to the electricity grid. The costs per energy unit used in the optimization process are normalized between 0 and 1.

The last term given in Expression (3) is related to the EIs' goal of external resource dependency minimization. Flexible energy components can be cate-

Table 1 Sets of each component type defined in Expressions (1)–(19)

Component	Set
All Components	\mathcal{C}
All Components connected to domain d	\mathcal{C}_d
External Component connected to domain d	\mathcal{X}_d
Fixed generation	\mathcal{A}
Fixed consumption	\mathcal{B}
Flexible generation	\mathcal{M}
Flexible consumption	\mathcal{N}
Time-shiftable consumption	\mathcal{L}
Storage	\mathcal{H}
Interconnector	\mathcal{K}

Table 2 An overview of KPIs used in the evaluation process

KPI	Description
External Energy Imported (<i>EEI</i>)	The amount of energy consumed from external sources, such as a gas boiler or the power grid.
External Energy Purchased (<i>EEP</i>)	Energy purchased from external sources e.g., energy bought from the Belpex spot market [6].
External Energy Exported (<i>EEE</i>)	The amount of energy provided to external sources, such as the power grid.
External Energy Sold (<i>EES</i>)	The revenue from energy sold to external sources, such as the power grid.
CO ₂ Emission (<i>CO₂E</i>)	The amount of CO ₂ emissions from used energy sources, such as a gas boiler or the power grid

gorized into two groups: internal and external. The third term in the objective function focuses on the minimization of the sum of external flexible energy generation and consumption, thus increasing self-sufficiency of EI.

5 Evaluation

In this section an evaluation of the discussed multi-vector optimization problem in Sect. 4 is provided. Before the experimental model can be set up and evaluated, Key Performance Indicator (KPI) need to be established and discussed, such that the results of each scenario can be measured and compared. In this evaluation, five KPIs are defined and outlined in Table 2.

The External Energy Imported (*EEI*) indicator provides an overview on how much energy is consumed, while the External Energy Purchased (*EEP*) shows the resulting costs. The *EEI* is the sum of energy imported from external sources over the entire simulation time frame T and is therefore an indicator for the self-sufficiency of the system, which is the reason why it is considered as KPI in this paper. Furthermore the *EEP* shows the cost of the systems' consumed energy, which is part of the optimization problems price objective as defined in Eq. (2) and is therefore considered a KPIs.

$$EEI_d = \sum_{t \in T} S_d^c(t), \quad (20)$$

$$EEP_d = \sum_{t \in T} S_d^c(t) \cdot p_c(t), \quad c \in \mathcal{X}_d. \quad (21)$$

In Eq. (21) the time dependable cost is denoted as $p_c(t)$ and describes the energy price in a specific time step t of time frame T . Further, in Eq. (20) and (21) $S_d^c(t)$ defines the amount of energy consumed from the specified external energy source during time step t . The External Energy Exported (*EEE*) shows the amount of energy provided to external sources. Together with the *EEI*, the *EEE* visualizes the strategy of consuming energy during low energy prices and injecting energy to external sources during price peaks. To further emphasize the impact on such strategies, the External Energy Sold (*EES*) show the financial gain of selling energy to external sources. The *EEE* and the *EES* are defined as follows:

$$EEE_d = \sum_{t \in T} D_d^c(t), \quad (22)$$

$$EES_d = \sum_{t \in T} D_d^c(t) \cdot p_c(t), \quad c \in \mathcal{X}_d, \quad (23)$$

where the sold amount of demanded energy per time step in Eq. (22) and (23) is denoted as $D_d^c(t)$ and the price paid for the individual time step t is defined as $p_c(t)$. To gain insight on the environmental impact of the multi-vector optimizer or in other words the impact on greenhouse emissions, the CO₂ Emission (*CO₂E*) is depicted as:

$$CO_2E_d = \sum_{t \in T} \sum_{c \in (\mathcal{M} \cup \mathcal{A})} S_d^c(t) \cdot r_c(t). \quad (24)$$

In Eq. (24) c denotes the component of the set of flexible and fixed generation sources ($\mathcal{M} \cup \mathcal{A}$), where the amount of consumed energy $S_d^c(t)$ is multiplied by the energy sources' CO₂ index $r_c(t)$ in time step t .

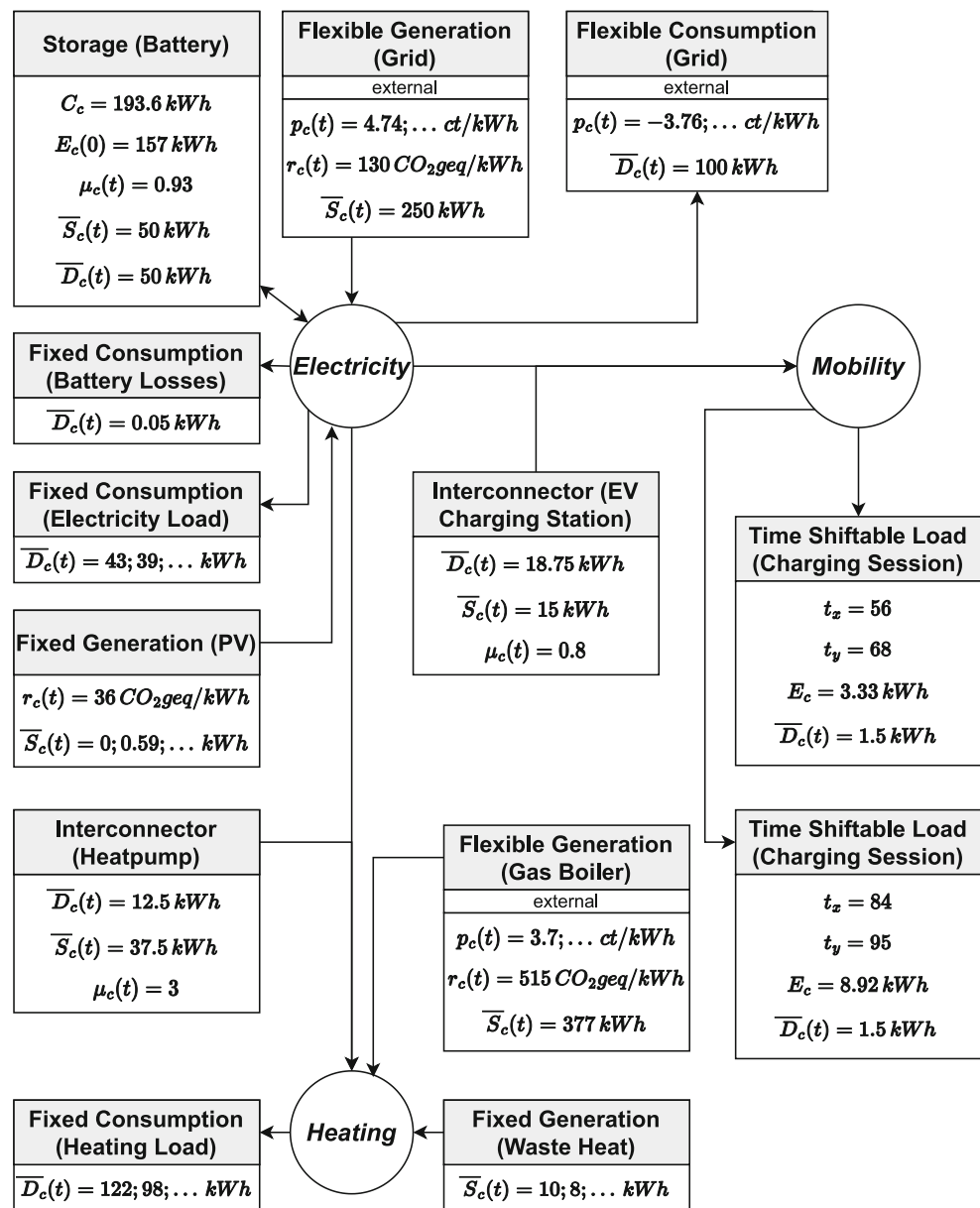
These KPIs were chosen in order to provide an overview of the energy flow, the economical influence as well as the environmental impact of the multi-vector optimizer. The following section provides a short overview of the underlying system's model as well as a comparison between the non-optimized case and the optimized case.

5.1 Energy Island model structure

In order to evaluate the approach proposed in Sect. 4, data from a real-world residential complex of multiple buildings in Ghent (Belgium) is used [4]. The data contains information of different devices installed in distributed facilities, such as PV generation data, charging and discharging battery data, but also meta-data such as capacity and energy conversion efficiency, EV charging stations, with consumption, arrival and departure time data of individual charging sessions, heat pump consumption data as well as heat and electricity consumption meters. The unique feature of this EI is its connection to the industrial chemical plant which can supply energy to the heating system. The plant can be considered as a waste heat source, i.e., that the EI consumes energy that would otherwise not be used. The energy from the waste heat source is not always available, thus often a gas boiler has to be activated additionally to meet heat demand.

Fig. 2 shows the structure of the model and selected parameters of individual components. The residential complex in Ghent is connected to the power grid via an external flexible generation and an external flexi-

Fig. 2 Components and domains in multi-vector optimization based on the data from Ghent EI [4]



ble consumption, which are limited by 250kWh and 100kWh respectively. Note that both, cost involved in the energy consumption and gains in the energy injection, are based on the Belpex spot market [6] and therefore are variable over time with a granularity of 1 hour time intervals. The PV system installed are fixed and cannot be influenced by the multi-vector optimizer and is therefore modelled as a fixed generation. Similarly, the electricity load, which cannot be controlled, is modelled as a fixed consumption. The CO₂ intensity of the power grid is assumed to be 130 CO₂ geq/kWh according to Electricity Maps [5], PV introduces a CO₂ intensity of 36 CO₂ geq/kWh and the gas boiler is modelled with a CO₂ intensity of 515 CO₂ geq/kWh.

In accordance with the provided data, the battery is modelled as a storage component with a capacity of 193.6kWh a symmetric conversion efficiency

μ_c of 0.93 and a charging and discharging limit of 50kWh. According to the provided data the initial state of charge is 157kWh. For simplification reasons, storage losses are assumed to be static, i.e., it is assumed, in every time step the battery loses 0.05kWh per time step of energy [13].

The EV charging station is an interconnector and connects the electricity domain with the mobility domain. The residential complex inherits 10 wall-boxes, each limited by a maximum input of 1.5kWh, corresponding to a charging power of 6 kW. Therefore, the entire EV charging station is limited to 15kWh. Furthermore, the EV charging station is assumed to have a constant conversion efficiency $\mu_c(t) = 0.8, \forall t \in \mathcal{T}$. The charging sessions depicted in Fig. 2 are dynamic and modelled according to the data provided, i.e., the individual sessions starting and departure time as well as the needed energy nec-

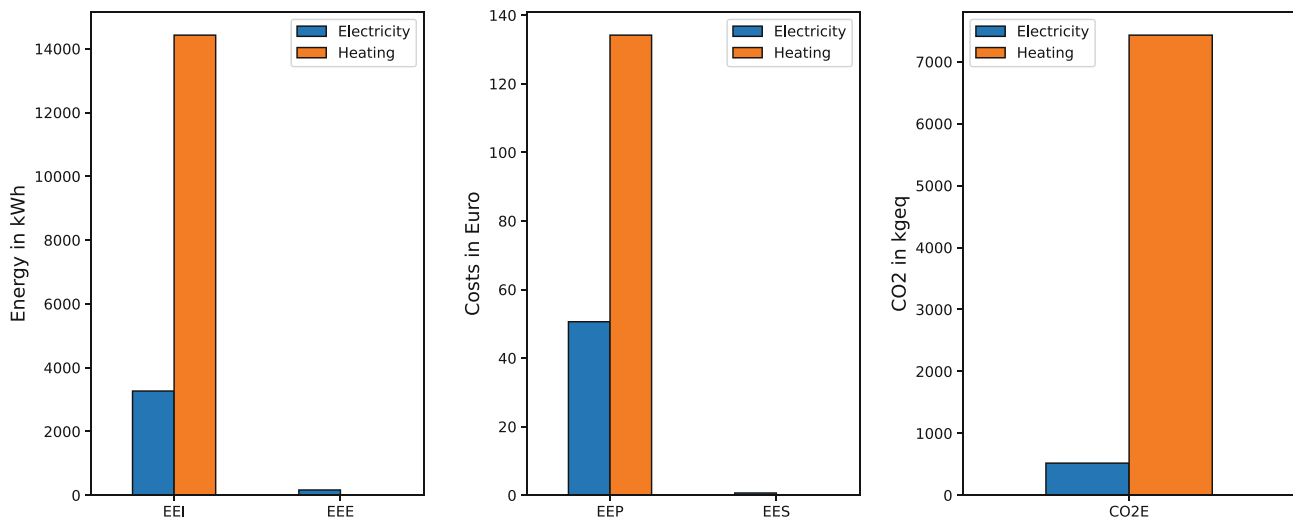


Fig. 3 KPIs values for the non-optimized scenario

essary for the charging session are extracted from the data. Furthermore it is assumed that the EV charging station only allows reserved charging sessions, i.e., it is ensured to acquire the starting and ending time of each charging session as well as the amount of energy consumed during this session beforehand.

According to the data, the heat pump used in Ghent has a coefficient of performance between 3.0 and 3.5, where the lower limit is chosen to have a more conservative view on the system. Furthermore, the heat pump is assumed to be limited by 12.5 kWh on the electrical side, since this is the maximum value found in the data set. It is assumed, that the heat pump is always available over the course of the simulation. In the heating domain the connection to the industrial chemical plant is modelled as a fixed generation, since the multi-vector optimizer cannot influence the output of the component itself, but can only control other components to react to the energy supply accordingly. Similarly, the heating demand of the residential sector is modelled as a fixed consumption. The gas boiler installed in the residential complex allows to additionally generate energy in the heating domain and is modelled as an external source. However, the boiler's generation is limited by 377 kWh, which is the maximum energy generated that can be found in the provided data. The unit cost of one kWh of energy is defined by the gas price provided by VREG [17].

For the evaluation of the model a time frame T from the 22th of April 2021 to the 29th of April 2021 is chosen, since during this time frame the original data shows a sufficient amount of electricity export as well as an considerable amount of gas and electricity import. The optimization time horizon \mathcal{T} consist of 96 time steps, which is equivalent to 1 day (each time step represents a 15 minute interval).

In the next subsection a description of two scenarios for evaluation is provided. At the moment of data collection, multi-vector optimization was not imple-

mented in the evaluated EI. Thus as a baseline, the first scenario represents the energy usage without optimization. The second scenario applies the proposed multi-vector optimization algorithm with the assumption that forecasting data is 100% accurate.

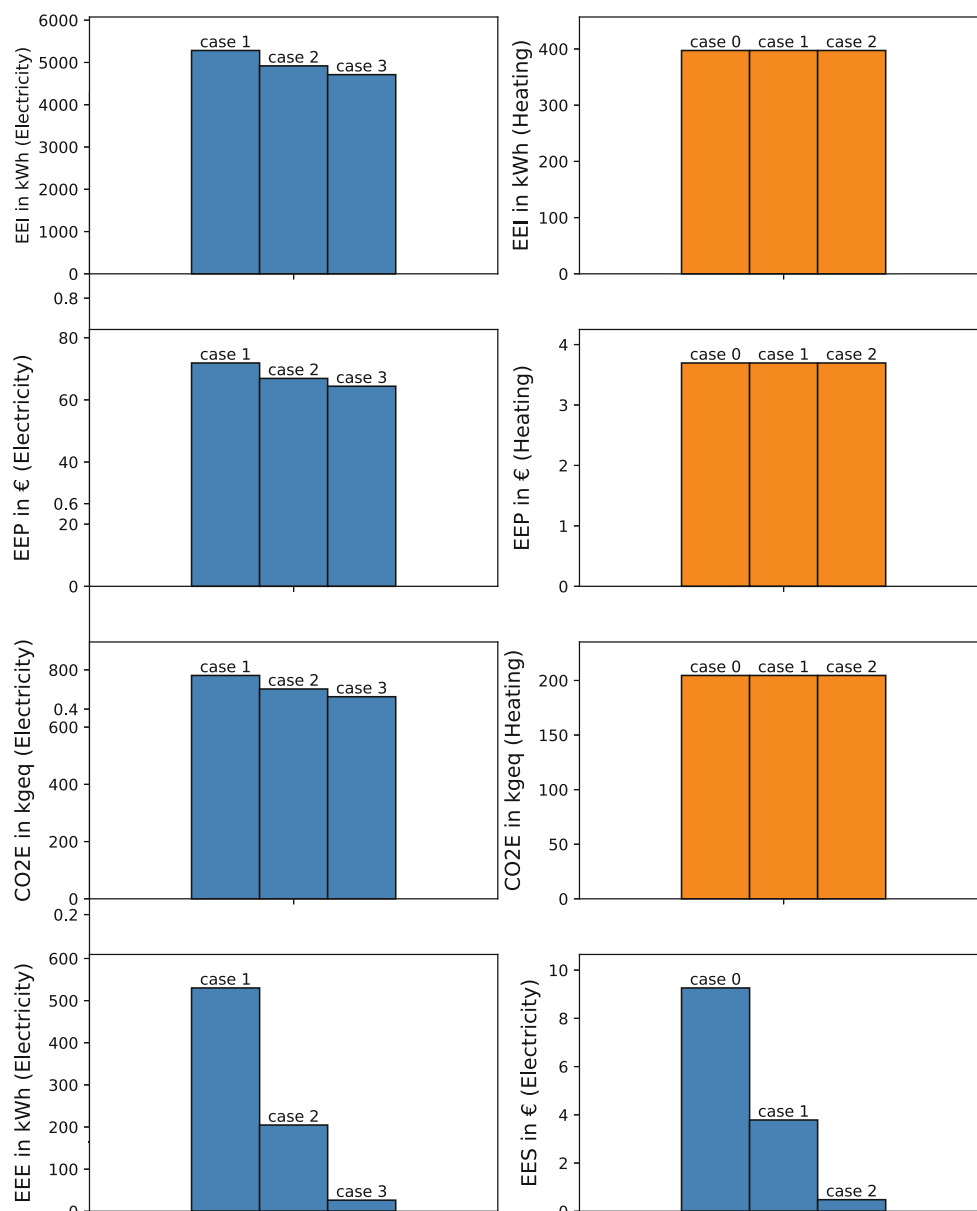
5.2 Scenario without optimization

For the non-optimized case, the provided data is evaluated based on the KPIs defined in Sect. 5. Fig. 3 shows KPIs calculated for the individual domains over the time frame of 22th of April 2021 to the 29th of April 2021. Note, the energy consumption and cost for energy imports are vastly higher for the heating domain than for the electricity domain. This is represented by the *Electricity* domain's (flexible generation representing the power grid) *EEI* value being lower than the *EEI* value of the *Heating* domain (gas boiler). This results in higher CO₂ emissions or a higher *CO₂E* value in the heating domain compared to the electricity domain. The high gas consumption in the heating domain is due to the under-utilization of the heat pump and the resulting over usage of the gas boiler, as well as not fully utilizing the waste heat source. Additionally, the CO₂ intensity of gas assumed in Sect. 5 is higher than the CO₂ intensity of the PV system or the power grid in April. Furthermore, the *EEE* value of this scenario shows that the exported energy is low compared to the imported energy, which results in a low *EES* value. This indicates that the battery is under-utilized and strategies such as buying at low electricity prices and injecting at price peaks are not considered.

5.3 Scenario with optimization

For the optimized scenario it is assumed that the forecasts provided are 100% accurate. Fig. 4 shows KPIs separated by the individual external sources with different weight configurations in the optimization pro-

Fig. 4 Results of the optimization for each case. Case 1 ($\omega_1 = 0, \omega_2 = 1, \omega_3 = 0$) prioritizes the minimization of financial costs, case 2 ($\omega_1 = 0.5, \omega_2 = 1, \omega_3 = 0$) considers the minimization of the financial costs and reduction of CO₂ emissions and case 3 ($\omega_1 = 0.5, \omega_2 = 1, \omega_3 = 0.1$) includes all three optimization objectives



cess. Three different configurations are chosen to show the impact of each individual objective. Case 1 defines the initial case of the setup, where only the price is considered as an objective ($\omega_1 = 0, \omega_2 = 1, \omega_3 = 0$). Compared to the non-optimization scenario the *EEI* of the heating domain is reduced heavily, due to the waste heat provided by the industrial chemical plant and the increased utilization of the heat pump, which additionally leads to an increase of the *EEI* value of the electricity domain.

In case 2, the objective related to CO₂ emissions is weighed with $\omega_1 = 0.5$, to emphasize on the reduction of CO₂ emissions, however still prioritizing the price objective. This results in a decrease of energy consumption, injection and therefore the financial gain as well as CO₂ emissions compared to case 1. Energy consumption from the grid results in an increase of CO₂ emissions, but the injection of energy into the

grid does not decrease the CO₂ emissions of the site. This makes the prospect of buying energy from the external power grid less desirable, despite the financial gain.

By increasing ω_3 in case 3 from 0 to 0.1 the avoidance of external consumption gains importance, however the financial as well as the CO₂ reduction incentive are still prominent. This results in further reduction of energy consumption/injection and therefore decreases CO₂ emissions. Both weights penalize the strategy of buying during low prices and selling at high peaks, since a) higher energy consumption is penalized by ω_3 and b) higher consumption results in higher CO₂ emissions, which is penalized by ω_1 .

Note that in case 1-3 the heating consumption does not change. The reason for this is that electricity prices during the time frame of the scenario are always cheaper than gas prices. This leads to the gas

generation already being minimized in case 1 and no further decrease can be observed in cases 2 and 3. Further note, that despite the gas boiler being more expensive and introducing more CO₂ emissions the gas boiler's heat generation cannot be reduced any further, since during certain time steps the heat demand cannot be matched by the heat pump and the waste heat source alone.

6 Conclusion

In this paper, a two-level optimization scheme for a multi-vector optimization is proposed for a group of distributed energy generation units and consumers. The multi-vector optimizer is an essential part of this scheme, allowing the control of multiple distributed devices or sub-systems. The multi-vector optimizer computes the optimal energy profile for devices in all domains, while the domain-specific optimizer schedule operation of devices considering domain-specific constraints. Generators and consumers are represented in the optimizer as abstract components. Several types of components are proposed which have different parameters and introduce different constraints to the optimization problem. This allows the modeling of real energy units, forecasts and different types of consumers. One benefit of this model lies in its abstraction level – it is not limited to a specific energy domain and can be used to model different types of energy sectors in facilities.

In order to show the effectiveness, the method is evaluated based on the data from a real-world EI in Ghent, Belgium. The scenario without optimization acts as a baseline, while the optimized approach shows that the optimal solution of the problem can be derived if no forecasting errors are encountered. Results show, the proposed multi-vector optimization scheme increases financial gain and reduces CO₂ emissions, by reducing gas consumption and increasing the utilization of the onsite heat pump and the provided waste heat energy.

In different cases, it was demonstrated that by increasing the weights of CO₂ reduction and self-sufficiency, the strategy of buying during low-cost hours and re-selling at price peaks gets increasingly unattractive. The multi-vector optimizer penalizes buying-and-re-selling strategies, since buying energy from the power grid introduces a higher consumption of CO₂, but injecting energy to the grid does not reduce the CO₂ emissions of the system. Furthermore, the self-sufficiency objective minimizes the amount of energy bought from and sold to the grid, which additionally penalizes the buying and re-selling strategy.

Note, for the optimization process a forecast accuracy of 100% is assumed. However, this is not realistic and the issue of forecasting errors needs to be tackled in future work. Additionally, this paper only focuses on the multi-vector optimization and the two-level

optimization scheme. The integration of domain-specific optimization schemes as well as the evaluation of cooperation between the multi-vector optimizer and multiple domain-specific optimizer needs to be established in future research.

Acknowledgements This paper has received funding by the European Union's Horizon 2020 research and innovation programme under grant agreement No. 957845: "Community-empowered Sustainable Multi-Vector Energy Islands – RENergetic"

Declarations

Funding This paper has received funding by the European Union's Horizon 2020 research and innovation programme under grant agreement No. 957845: "Community-empowered Sustainable Multi-Vector Energy Islands – RENergetic"

Conflict of Interest The authors declare that they have no competing interests.

Availability of data and materials The data used in the evaluation is partially available under: https://zenodo.org/record/5155659#.ZBRJ_i-HJpQ. The full dataset used in the paper is available upon reasonable request from the authors.

Authors' contributions The authors SG and MB contributed equally to the paper. SG contributed to the methodology formulation and MB run experiments for the evaluation of the results. HdM provided supervision and review of the paper. The authors read and approved the final manuscript.

Funding Open Access funding enabled and organized by Projekt DEAL.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

1. Agnetis A, de Pascale G, Detti P, Vicino A (2013) Load Scheduling for Household Energy Consumption Optimization. *IEEE Transactions on Smart Grid* 4(4):2364–2373, <https://doi.org/10.1109/TSG.2013.2254506>, <http://ieeexplore.ieee.org/document/6509468/>
2. Aman S, Simmhan Y, Prasanna VK (2013) Energy management systems: state of the art and emerging trends. *IEEE Communications Magazine* 51(1):114–119, <https://doi.org/10.1109/MCOM.2013.6400447>, <http://ieeexplore.ieee.org/document/6400447/>
3. Danner D, Seidemann J, Lechl M, de Meer H (2021) Flexibility disaggregation under forecast conditions. Association for Computing Machinery, New York, NY, USA,

- e-Energy '21, p 27–38, <https://doi.org/10.1145/3447555.3464851>, <https://doi.org/10.1145/3447555.3464851>
4. De Mulder, Chaim 2021 electricity and heat demand data for a city district (belgium). https://zenodo.org/record/5155659#.ZBRJ_i-HJpQ
 5. Electricity Maps Electricity maps. <https://app.electricitymaps.com/map>
 6. Elexys Belpex spot prices. <https://my.elexys.be/MarketInformation/SpotBelpex.aspx>
 7. Fridgen G, Keller R, Körner MF, Schöpf M (2020) A holistic view on sector coupling. *Energy Policy* 147:111,913, <https://doi.org/10.1016/j.enpol.2020.111913>, <https://www.sciencedirect.com/science/article/pii/S0301421520306248>
 8. Gautier A, Jacqmin J, Poudou JC (2018) The prosumers and the grid. *Journal of Regulatory Economics* 53(1):100–126, <https://doi.org/10.1007/s11149-018-9350-5>, <http://link.springer.com/10.1007/s11149-018-9350-5>
 9. Guo Y, Pan M, Fang Y (2012) Optimal Power Management of Residential Customers in the Smart Grid. *IEEE Transactions on Parallel and Distributed Systems* 23(9):1593–1606, <https://doi.org/10.1109/TPDS.2012.25>, <http://ieeexplore.ieee.org/document/6127869/>
 10. Han O, Ding T, Mu C, Jia W, Ma Z (2022) Coordinative optimization between multiple data center operators and a system operator based on two-level distributed scheduling algorithm. *IEEE Internet of Things Journal* <https://doi.org/10.1109/JIOT.2022.3188353>
 11. Liu Y, Gao S, Zhao X, Zhang C, Zhang N (2017) Coordinated operation and control of combined electricity and natural gas systems with thermal storage. *Energies* 10(7), <https://doi.org/10.3390/en10070917>, <https://www.mdpi.com/1996-1073/10/7/917>
 12. Maroufmashat, Taqvi, Miragha, Fowler, Elkamel (2019) Modeling and Optimization of Energy Hubs: A Comprehensive Review. *Inventions* 4(3):50, <https://doi.org/10.3390/inventions4030050>, <https://www.mdpi.com/2411-5134/4/3/50>
 13. Munzke N, Schwarz B, Büchle F, Hiller M (2021) Evaluation of the efficiency and resulting electrical and economic losses of photovoltaic home storage systems. *Journal of Energy Storage* 33:101,724, <https://doi.org/10.1016/j.est.2020.101724>, <https://www.sciencedirect.com/science/article/pii/S2352152X20315619>
 14. Ramsebner J, Haas R, Ajanovic A, Wietschel M (2021) The sector coupling concept: A critical review. *WIREs Energy and Environment* 10(4), <https://doi.org/10.1002/wene.396>, <https://onlinelibrary.wiley.com/doi/10.1002/wene.396>
 15. Rastegar M, Fotuhi-Firuzabad M, Moeini-Aghtai M (2016) Developing a two-level framework for residential energy management. *IEEE Transactions on Smart Grid* 9(3):1707–1717, <https://doi.org/10.1109/TSG.2016.2598754>
 16. Sun S, Dong M, Liang B (2016) Distributed real-time power balancing in renewable-integrated power grids with storage and flexible loads. *IEEE Transactions on Smart Grid* 7(5):2337–2349, <https://doi.org/10.1109/TSG.2015.2445794>
 17. VREG Vreg gas prices. https://dashboard.vreg.be/report/DMR_Prijzen_gas.html
 18. Wu C, Gu W, Xu Y, Jiang P, Lu S, Zhao B (2018) Bi-level optimization model for integrated energy system considering the thermal comfort of heat customers. *Applied Energy* 232:607–616, <https://doi.org/10.1016/j.apenergy.2018.09.212>, <https://linkinghub.elsevier.com/retrieve/pii/S0306261918315344>
 19. Zhai J, Wu X, Zhu S, Yang B, Liu H (2020) Optimization of integrated energy system considering photovoltaic uncertainty and multi-energy network. *IEEE Access* 8:141,558–141,568, <https://doi.org/10.1109/ACCESS.2020.3013396>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Stepan Gagin, received his M.Sc. Degree in Computer Science from University of Passau, Germany, in 2021. After graduation, he continues to work at the chair of Computer Networks and Computer Communications at the University of Passau. Currently, he is participating in the EU research project REnergetic supporting the development of ICT infrastructure for Energy Islands. His research focuses on applications of artificial intelligence and optimization in energy systems.



Michael Bettermann, received his Bachelor and Master's degrees from the University of Passau, Germany, in 2019 and 2022. He is currently working on the chair of Computer Networks and Computer Communications with Prof. Hermann de Meer. His research interests include optimization and digitalization of energy systems and the smart grid.



Hermann de Meer, received his Ph.D. from University of Erlangen-Nuremberg, Germany, in 1992. He had been an Assistant Professor at Hamburg University, Germany, a Visiting Professor at Columbia University in New York City, USA, and a Reader at University College London, UK. He has been appointed as Full Professor at the University of Passau, Germany, and as Honorary Professor at University College London, UK, since 2003. His research interests include energy systems, network virtualization, IT security, smart grid, digitalization of energy systems, computer networks and distributed systems.