Distributed Topology Optimization for Agent-based Peer-to-Peer Energy Market

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***Abstract*— Due to the ongoing energy transition the coordination of the power flow is shifting from centralized to decentralized, where autonomous systems such as software agents interact with each other. However, in contrast to centralized approaches, the communication effort of the agents significantly increases to share information among all agents, thereby an efficient communication approach in multi-agent systems is necessary. This paper proposes a novel distributed topology optimization approach that minimizes the communication effort in a peer-to-peer energy market, where agents buy and sell energy to efficiently dispatch energy flow. The approach is applied to a multi-agent system and simulations on an IEEE-33 and IEEE-119 bus network show that the proposed approach results in a higher financial gain with reduced communication effort compared to not applying the topology optimization. Overall, this approach has the potential to enhance the efficiency and scalability of energy management systems in a decentralized energy market.**

Keywords—decentralized control, communication, topology optimization, peer-to-peer energy market

I. Introduction

The increasing integration of renewable energy sources and the growing number of energy consumers, such as electric vehicles or heat pumps, have led to significant challenges in the operation and management of modern power grids. Especially a reliable energy supply by photovoltaic systems and energy dispatch among households will be a major challenge. Traditional centralized approaches for energy dispatch may not be scalable and flexible enough to handle the complexities of modern power grids [1]. Furthermore, households are not actively involved into grid control, which can lead to non-grid-friendly behaviours and a reduction in overall comfort. To overcome the problem, peer-to-peer energy markets exist where households can trade energy locally, as presented in [2]. With the emergence of distributed energy resources (DER) and advancements in communication and control technologies, agent-based approaches have gained attention as promising solutions for addressing these challenges [3].

Agent-based approaches leverage the capabilities of autonomous agents, e.g. generators, loads, and energy storage systems, to autonomously make decisions and interact with each other in approximately real-time [4]. These agents can communicate, coordinate, and collaborate to optimize the operation of the power grid. One key aspect of agent-based approaches is the design of the agent´s topology [5]. The agent´s topology describes which agents are communicating and interacting with each other to achieve efficiency and coordination. In addition to the agent´s topology, the grid architecture exists which describes the electrical connection between households. In this case, the grid architecture is given by an IEEE-33 as well as an IEEE 119 bus-network [6].

A. Problem Formulation

Besides the benefits of decentralization of the energy market, it poses new challenges as well. Individual market participants are represented by multi-agent systems (MAS), which exchange information with other agents about the grid state, energy offers and energy demand. The task of energy trading between participants is distributed among the participating agents. To accomplish this, the participating agents must be capable of self-optimization and communication [7]. The more agents in a defined MAS that communicate and trade with one another, the closer the trading results are to the mathematical optimum, which can be achieved by applying central optimization [5]. On the other hand, a high number of interacting agents results in larger computational time which can be disadvantageous in case of volatile energy production by DER [8]. Thus, it is necessary to limit the number of interacting peers. This conflict can be addressed by mathematically optimizing the topology, which can improve the efficiency and scalability of the decentralized energy market.

B. Contribution of the paper

In this paper, we propose a reliable distributed topology optimization concept for agent-based energy trading in power grids. The concept aims to minimize agent communication while achieving better results compared to a scenario without topology optimization. The concept is based on defined properties of households to determine the most potential trading partners. It is implemented in an IEEE-33-bus-network representing a standardised low-voltage-grid. The results are compared to the scenario where topology optimization is not applied to demonstrate the efficiency of the concept.

C. Requirements of the distributed topology optimization

To guide the approach´s design and to enable a structured verification, requirements are defined which are presented in this subsection. As a first requirement (R1), the system should minimize the agents' communication while still achieving better results than what would be possible without topology optimization. The minimization should be employed decentrally. The second requirement (R2) describes that the topology optimization should be designed in combination with an agent-based peer-to-peer energy market to test the optimization´s performance. R3 represent the privacy of the households. Thus, households' properties, e.g., the yearly energy consumption, should be raised anonymously, and the numbers should be abstracted. As an additional requirement to the properties, the concept should consider the grid´s structure and be able to react dynamically to changes in the structure, e.g. the position of the power switches (R4).

Furthermore, R5 describes the requirement that the approach should be able to handle an agent´s failure to ensure the concept´s reliability. A further requirement (R6) is the simplicity of the approach. This is important to achieve a higher software quality as well as a better maintenance of the code. In addition, simple concepts meet more acceptance of distributed system operators who are responsible for implementing the system in real low-voltage grids.

II. State-Of-The-Art

Several approaches for optimizing the topology applied in a peer-to-peer energy market already exist in the literature. In this study, we analyse these approaches considering the requirements outlined in subchapter I.C.

The authors of [9] present an agent system that optimizes its own energy consumption by applying internal optimization. Furthermore, an approach for grid control in an island grid using corresponding sensors is implemented. Decentralized optimization of energy flow is the focus of this publication, while requirements such as topology optimization are not considered. In contrast to [9], the authors of [10] present a topology optimization using a few larger renewable generation plants as energy producers in addition to consumers. Island grids are created based on these generators. This publication includes topology optimization of the agent´s communication; however, it is a one-time process that cannot be dynamically adapted to changing conditions. In [11], the topology optimization of [10] is further developed by considering the characteristics of grid participants to create optimized island grids that reflect their individuality. However, this approach fails to address dynamic grid changes, such as the failure of cables or agents.

In [12], agents are introduced that control renewable energy generators to operate an island grid, with the agents collaborating to maintain grid stability. This publication focuses on the use of an agent system implemented within the Java Agent Development Framework (JADE) [13]. However, it does not incorporate communication cost minimization into the optimization process.

In the publication of [14], a large power grid is partitioned into island grids with a focus on energy dispatch and the handling of partial failures within those grids. The optimization of network topology and energy dispatch are both considered, and there is an approach for responding to dynamic network changes. However, this publication does not utilize an agent system. Thus, a failure of a subsystem can´t be handled.

The authors of [15] present a topology optimization using the Dijkstra algorithm. Thus, the agents can conduct decentralized grid control using the nearest power provider. Although no concrete time frames were determined for grid control, this publication addresses the need for efficient and reliable grid control. Besides the presented concept in [15], the authors of [16] present a concept which adapts the topology to dynamic grid changes using the Dijkstra algorithm. This is intended to ensure a stable and reliable power grid. This work stands out by introducing a plug-and-play principle for expandability of the power grid, which was not addressed in the other publications. However, [15] and [16] are not applied to a peer-to-peer energy market.

[17] proposes a method for reconfiguring the network topology in response to critical grid states, which involves isolating faults to ensure grid operation. The approach responds to dynamic network changes and utilizes an agent system. However, a centralized topology with a master agent was employed instead of a decentralized topology. A summary of these results from the literature research is presented in TABLE I.

TABLE I Analysis of the literature regarding the fulfillment of the requirements, where "X" represents a fulment and a "-" No Fulfilment

	R1	R2	R3	R4	R5	R6
[9]	-	X	X	-	X	-
[10]	X	X	-	-	-	X
[11]	X	X	X	-	-	-
[12]	X	X	X	-	-	X
[14]	X	-	X	X	-	-
[15]	X	-	-	X	X	X
[16]	X	-	-	X	-	X
[17]	X	-	-	X	X	X

Although various works on the topic of topology optimization of an island grid exist, the requirements presented in I.C have not yet been fully met. This research gap is addressed in this paper.

III. Method

The development of the presented approach follows a modelling cycle and is based on four steps. In the first step, the real system - in this case, the low-voltage grid - is analysed to identify the network participants, their tasks, and interests. Based on the resulting structures, a preliminary model is constructed to represent a low-voltage grid and the grid participants therein. In the second step, this preliminary model is transformed into a mathematical model by parameterizing and quantifying the properties of individual grid participants and the boundary conditions of the preliminary model, while also making assumptions about the limitations of the preliminary model. In the third step, the mathematical model is implemented in JADE and the validation of the developed approach represents the fourth step.

IV. Agent modelling

This chapter presents the concept of topology optimization, applying the first two steps of the presented modelling cycle. Since the topology optimization should be applied to a peer-to-peer energy market, this concept is presented as well.

A. Peer-to-Peer Energy Market

There are several approaches for a peer-to-peer energy market design as presented in [18]. One of them consists of agents which trade energy among each other without having a central coordination instance. This trading is based on competition since every agent seeks the maximum own profit In peer-to-peer markets are classified into fully connected and partly connected [5]. To provide a scalable system, a partly connected peer-to-peer market is applied. In [19] it was shown that competitive trading algorithms are more efficient for use in competitive environments, such as trading energy quantity and price. Therefore, a competitive trading algorithm is applied for the presented peer-to-peer energy market.

According to [5], a competitive leader-follower game is one of the most efficient competitive trading algorithms for designing the pricing model of the smart grid control, and is therefore used for the present study. In this work, a leader l is an agent with surplus energy. Hence, leaders are willing to offer energy to other participants and begin the trading by offering energy. Agents that need energy decide how much of the offered energy they are willing to buy and act as followers f. The presented leader-follower game is mathematically defined as follows according to [20]:

$$G = \{L \cup F, \{X_l\}_{l \in L}, \{X_f\}_{f \in F}, \{U_l\}_{l \in L}, \{U_f\}_{f \in F}\} \tag{1}$$

Let L be the set of offering prosumers acting as leaders l, and F be the set of demanding prosumers acting as followers f. Let X_l and X_f represent the strategy sets of leaders and followers, respectively. Further, let U_l and U_f represent the utility functions of leaders and followers, respectively, which mathematically describe the agent´s optimization objective. Consequently, every agent provides its own strategy and own utility function which is unknown to other agents. To avoid double-selling of energy, the energy amount is locked for trading as soon as a leader sends an energy offer until they receive a response. The followers have the following objective function to minimize their energy costs:

$$U_f = \min \sum_{f \in F} E_{lf,k} \cdot P_{fl,k}, \forall k \in K \tag{2}$$

Where E_{lf} represents the energy flow from l to f and P is the energy price that f must pay to l. The index k describes the discrete 15-minute time interval as a subset of K, the total simulation time. Unlike followers, leaders aim to maximize the price of the sold energy. Thus, they pursue the following objective function:

$$U_l = \max \sum_{f \in F} E_{lf,k} \cdot P_{fl,k}, \forall k \in K \tag{3}$$

If there is not enough energy offered, the follower will proactively send their remaining energy demand to other leaders.

One challenge of decentralized optimization is the decision-making without a central authority. Thus, a criterion must be defined for when the negotiation is completed. Such a termination criterion is presented in [21], where the difference in price from the previous iteration step is used. When the difference falls below a defined value ε, the iteration ends. The termination criterion is mathematically described as follows:

$$\left|P_{fl,k+1} - P_{fl,k}\right| < \varepsilon \tag{4}$$

If the final criterion has not been met, counteroffers will be created and sent. Once the final criterion has been reached, an acceptance message will be sent and energy delivery, as well as money transfer, can take place.

Moreover, in case of an energy deficit that cannot be met by other prosumers, the prosumer must procure energy from an external energy supplier at a fixed energy price of 0.36 €/kWh. If a prosumer is unable to sell its surplus energy within the 15-minute trading interval, the surplus energy must be fed into the grid, and the prosumer receives a feed-in tariff of 0.08 €/kWh. Thus, the maximum and minimum prices of the energy trading are set to the feed-in-tariff and external energy price, respectively. The fixed prices are based on current electricity prices in Germany and can be replaced variably.

In addition, the trading interval consists of trading cycles with a duration of five seconds. Within these five seconds, every follower can optimize the incoming energy offers received in the previous trading cycle and send reoffers or rejects if necessary. Every leader can either create new energy offers or calculate reoffers based on received reoffers of the follower. In addition, if the end criterium is reached, both, leader and follower can send energy results. Thus, the number of actions an agent can conduct within a trading interval is limited to m

$$m = \frac{t_{int}}{t_{tcyc}} = \frac{15\ min}{5\ s} = 180 \tag{5}$$

The value of 5 s is chosen because by applying lower trading-cycle duration, agents might not be able to finish all their computational tasks, including sending messages. This design of a peer-to-peer energy market is called discrete call auctions. Regener et al. [18] show that discrete call auctions result in a higher financial gain of the agents than continuous ones. Thus, the discrete call auction is applied in the work.

B. *Influence Factors for the topology optimization*

The topology optimization is an algorithm every agent executes when a 15-minute trading interval starts. The algorithm yields a list of agents which is sorted by relevance for the trading. Every agent has its own list which serves as a guide for the agents to determine the order in which they offer energy to their trading partners. To determine the relevance of every agent, influence factors need to be established which is described in the current subchapter.

Yearly energy consumption: The yearly energy consumption of a household plays a crucial role in determining whether a household can be a potential buyer of energy. This information is critical for energy producers and traders to assess the potential profitability of selling energy to the household. A household with a high yearly energy consumption is more likely to have a significant energy demand, which makes it a potential buyer of energy.

Flexible Energy Systems: Flexible energy systems of households refer to the ability of households to actively participate in the power grid operation by adjusting their energy consumption or generation based on external signals or incentives. These flexible energy systems can include various DER such as photovoltaic (PV), battery energy storage systems (BESS), and electric vehicles (EV). The availability and behavior of flexible energy systems are crucial factors that can significantly impact the performance of the peer-to-peer energy market. Therefore, they are considered as one of the influencing factors in the presented distributed topology optimization approach.

Solar Irradiation: Weather data, including meteorological measurements such as temperature, wind speed, solar irradiance, and precipitation, plays a crucial role in the operation of power grids. Since in low-voltage grids, only PV plants as DER exist, solar irradiation r_s is taken as the measure for the weather data. r_s has a direct impact on the generation and consumption of electricity, as well as the availability and performance of DERs. Therefore, incorporating r_s into the distributed topology optimization approach is essential for accurate decision-making and optimal power grid operation. r_s will be forecasted for the next 15 min in the region where the low-voltage grid is implemented.

Thus, the yearly energy consumption, the flexible energy systems, and the forecasted solar irradiation are considered as influencing factors into the presented topology optimization.

C. Mathematical Model of the Influencing factors

To optimize the agent´s communication topology, it is important to quantify the influencing factors described in IV.B above. Since only agents having an energy surplus can start a negotiation, the influencing factors are rated based on producer´s perspective. A household that consumes a significant amount of energy annually is more likely to be an attractive negotiation partner as they have a high potential for energy consumption. This can result in a more stable and profitable trading partnership. Because of privacy issues, other agents are not allowed to know about the exact energy consumptions of other households. Consequently, the consumption rate is discretized and abstracted into High (H), medium (M) and low (L). According to [22], the energy yearly consumption c_y per household can be rated between 2 MWh to 5 MWh.

In addition to the consumption rate, the amount of flexible systems of a household is important since a high share of flexible energy systems increases the possibility to buy energy on a peer-to-peer energy market. Thus, the percentage of flexible energy systems s_f in relation to all energy consuming systems of a household is classified into H, M, and L as well.

According to the three-level classification of the c_y and s_f, the r_s is levelled in H, M and L as well. Therefore, the solar irradiation range of the actual day is divided into three equal parts (terciles) based on the maximum value of $r_s = r_{s_{max}}$. Thus, $r_{s_{max}}$ of the current day needs to be forecasted. The forecasted solar irradiation for the next 15 minutes is levelled into these terciles, where values in the first tercile labelled as H, the second in M and the third in L. A high solar irradiation level results in a lower priority level, as many other PV plants are likely to produce a significant amount of energy and offer it to other agents, thereby reducing the energy price paid by other consumers. This correlation is only given when consumers provide a flexible energy consumption to react dynamically to market prices. Based on the classification of yearly consumption, flexible energy systems, and solar irradiance, a priority score (PS) can be determined. The higher a household´s priority score, the more likely it is to buy energy. PS is composed of the combination of the levels of c_y, s_f and G, consequently it can range from H-H-H to L-L-L, encompassing all possible combination in between. If an agent´s failure is detected, it is not listed on the priority list generated out of the topology optimization. The quantified classification is presented in TABLE *II*.

TABLE II CLASSIFICATION OF YEARLY CONSUMPTION PER HOUSEHOLD, FLEXIBLE ENERGY SYSTEMS AND SOLAR IRRADIATION INTO HIGH(H), MEDIUM (M) AND LOW(L)

Levels	**Yearly consumption per household c_y**	**Percentage of flexible consuming systems s_f**	**Solar irradiation** r_s
H	$c_y > 5\,MWh$	$s_f > 67\,\%$	$\frac{r_s}{r_{s_{max}}} < 33\,\%$
M	$2\,MWh < c_y < 5\,MWh$	$33\% < s_f < 67\,\%$	$33\% < \frac{r_s}{r_{s_{max}}} < 67\,\%$
L	$c_y < 2\,MWh$	$s_f < 33\,\%$	$\frac{r_s}{r_{s_{max}}} > 67\,\%$

The process from starting the MAS to the start of the peer-to-peer energy trading is depicted as an activity diagram in Fig. 1. After requesting the Agent Management Service (AMS) to get a list of all agents operating in the current system, every agent sends its consumption and flexible-energy-systems level as a broadcast to all agents. After receiving others agent´s consumption and flexible-energy-systems levels, the first trading interval can start. At the beginning of every trading interval, the weather forecast is called. Then, the priority list can be calculated.

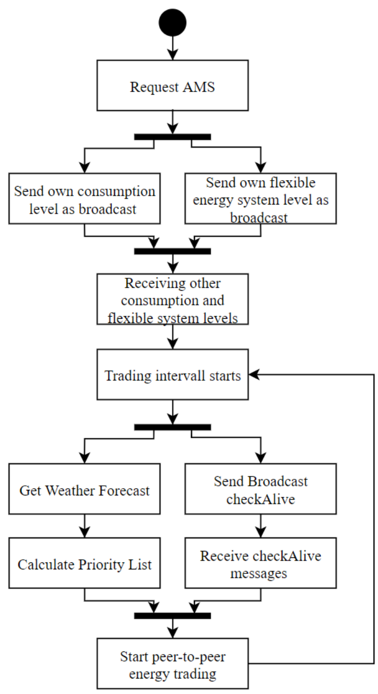

Fig. 1. *UML-activity diagram of the topology optimization*

Simultaneously, a simple *checkAlive* message is sent as broadcast message. If an agent does not return the *checkAlive* message, the agent is declared as failed and consequently will not be listed at the priority list. Once all these steps have been completed, the actual peer-to-peer energy trading can begin and continue until the start of the next trading interval.

V. SIMULATION

This chapter presents the simulation, its periphery as well as its results. Thus, the third and fourth step of the applied modelling cycle is presented.

A. *Simulation and Simulation Periphery*

To simulate the developed topology optimization both, a standardised low-voltage grid according to IEEE-33-test grid and a IEEE-119-test grid was used [6]. These test grids provide 33 and 119 nodes, respectively. To each node, different energy systems are assigned, which are based on the 2050 expansion scenario of the electrical distribution grid [23]. According to [23] and [22] 80 to 90 % of residential buildings will be equipped with a PV system in 2050 and will be able to feed in or offer energy accordingly if there is sufficient solar radiation. The other households can only demand energy. The energy resource are modelled according to the findings of [24] as black-box models. A projected consumption pattern from the year 2050 is used to represent consumer´s behaviour. The household´s yearly energy consumption is randomly assigned to the households. The agent-based topology optimization as well as the peer-to-peer energy market is implemented in Eclipse utilizing JADE. The simulation is performed using the simulation environment Agent.Workbench [25].

The proposed approach is validated, and its advantages are quantified by comparing it with a decentralized energy dispatch in which energy offers are sent by agents in a randomly set order (referred to as RS). Furthermore, four key performance indicators (KPIs) are evaluated across all scenarios: the RS method and the topology-optimized (TO) agent selection, both of which are applied to IEEE-33 and IEEE-119 test grid.

The first KPI depicts the average financial profit (FP) per prosumer, representing each leader's monetary gain in the energy market. The second KPI, the number of messages (NM) exchanged daily, signifies the system's communication load. The third KPI, the average performance (AP), evaluates the efficiency by relating financial gains to communication efforts. The last KPI assesses the nominated standard deviation of received messages, highlighting prosumer discrimination (DF). These KPIs are formulated mathematically in [19].

B. *Results*

1) *Presentation of Results*

The results of the peer-to-peer energy trading using TO compared to a RS are presented in TABLE *III*. The proposed TO method results in a higher financial profit for agents offering energy due to the improved selection of trading partners. Additionally, there's a noticeable reduction in the NM exchanged among agents, indicating the successful achievement of the approach's objective to minimize communication. In terms of scalability, when agents negotiate based on a TO in the IEEE 119 test grid, they require only 378 messages per prosumer daily for negotiations. This contributes to a better AP. When comparing TO with RS, the performance of DF is worse due to prioritization of prosumers in both test grids.

TABLE III - RESULTS OF THE PEER-TO-PEER-ENERGY TRADING USING TOPOLOGY OPTIMIZATION (TO) AND RANDOM SELECTION (RS)

	Grid	FP (€/kWh)	NM	AP	DF
TO	**IEEE 33**	0,254	226	0,122	0,4231
RS	**IEEE 33**	0,249	707	0,035	0,301
TO	**IEEE 119**	0,265	378	0,070	0,9134
RS	**IEEE 119**	0,248	1217	0,020	0,5957

Regarding the differences between 33 prosumers and 119

Beyond the recorded performance metrics, Fig. 2. also depicts the energy price aggregated for all 119 prosumers for every 15 min trading period. The graph suggests that the prosumer attains a more favorable average price due to improved communication with more suitable trading partners, as prioritized on the list.

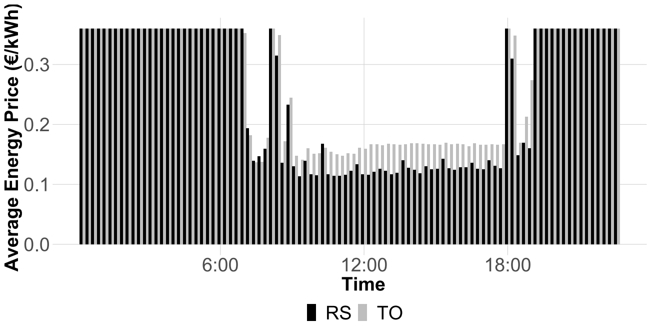

Fig. 2. *Energy prices of TO and RS during one day for an IEEE-119 bus-network*

The RS-simulation was conducted three times for each test grid to show that the results are reproducible. The variation among these three identical tests was quantified using the R^2 value of the matched prices. Consequently, the average R^2 value across all tests was found to be 0,9935.

2) *Result´s Discussion*

The presented TO provides a list of agents to communicate with aiming to trade energy. The list is sorted by priority to reduce communication effort. However, a household providing a high consumption potential is offered a lot of energy by agents having surplus energy. Thus, the household has to reject some energy offers which exceed its own energy need. Thus, there is still a communication overhead. This communication overhead can be reduced by applying learning algorithms or more complex dependencies. This however would reduce the simplicity of the presented concept. Furthermore, all agents are required to calculate a priority list, which remains the same for agents within the same low-voltage grid. However, if agents trade energy to households situating in other low-voltage grid, the distance between agents should be considered in the priority list. In addition, every agent can add personal preferences into the PS, e.g., the size of others consumer. Consequently, every prosumer needs its own priority list.

VI. Conclusion

This paper presents a decentralized agent-based topology optimization which is applied to an agent-based peer-to-peer energy market. The topology optimization represents an algorithm which is based on three influencing factors and provides a priority list for every agent, i.e. an order of other agents which are the most attractive trading partners. The concept was simulated on an both, an IEEE-33 as well as IEEE-119 bus network. The simulation has demonstrated the benefits of applying decentral topology optimization in a local peer-to-peer energy market. The results clearly indicate that agents can achieve higher financial profits by using the proposed approach compared to not using it. Moreover, the reduction in the number of exchanged messages further enhances the efficiency and scalability of the energy management system. The results of this study contribute to advancing the understanding of decentralized energy systems and provide practical insights for the implementation of effective topology optimization strategies.

In future work, the combination of topology-optimization and energy trading will be extended to decentral congestion management. Thus, agents can manage energy dispatch and additionally identify as well as manage congestions in a decentralized manner. In addition, the approach will be further adjusted to consider discrimination issues of prosumers.

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VII. References

[1] Zhou, Q., Shahidehpour, M., Paaso, A., Bahramirad, S., Alabdulwahab, A., and Abusorrah, A. 2020. Distributed Control and Communication Strategies in Networked Microgrids. *IEEE Commun. Surv. Tutorials* 22, 4, 2586–2633.

[2] Mengelkamp, E. 2019. *Engineering Local Electricity Markets for Residential Communities*.

[3] Paudel, A., Sampath, L. P. M. I., Yang, J., and Gooi, H. B. 2020. Peer-to-Peer Energy Trading in Smart Grid Considering Power Losses and Network Fees. *IEEE Trans. Smart Grid* 11, 6, 4727–4737.

[4] Derksen, C., Linnenberg, T., Unland, R., and Fay, A. 2013. Unified Energy Agents as a Base for the Systematic Development of Future Energy Grids. In *Multiagent system technologies*. Springer, Berlin.

[5] Nedic, A., Olshevsky, A., and Rabbat, M. G. 2018. Network Topology and Communication-Computation Tradeoffs in Decentralized Optimization. *Proc. IEEE* 106, 5, 953–976.

[6] Baran, M. E. and Wu, F. F. 1989. Network reconfiguration in distribution systems for loss reduction and load balancing. *IEEE Trans. Power Delivery* 4, 2, 1401–1407.

[7] Yang, T., Yi, X., Wu, J., Yuan, Y., Di Wu, Meng, Z., Hong, Y., Wang, H., Lin, Z., and Johansson, K. H. 2019. A survey of distributed optimization. *Annual Reviews in Control* 47, 278–305.

[8] Sarafraz, M. S. and Tavazoei, M. S. 2021. A Unified Optimization-Based Framework to Adjust Consensus Convergence Rate and Optimize the Network Topology in Uncertain Multi-Agent Systems. *IEEE/CAA J. Autom. Sinica* 8, 9, 1539–1548.

[9] Leo, R., Milton, R. S., and Kaviya, A. 2014. Multi agent reinforcement learning based distributed optimization of solar microgrid. In *2014 IEEE International Conference on Computational Intelligence and Computing Research*. IEEE, 1–7. DOI=10.1109/ICCIC.2014.7238438.

[10] Che, L., Zhang, X., Shahidehpour, M., Alabdulwahab, A., and Al-Turki, Y. 2017. Optimal Planning of Loop-Based Microgrid Topology. *IEEE Trans. Smart Grid* 8, 4, 1771–1781.

[11] Cortes, C. A., Contreras, S. F., and Shahidehpour, M. 2018. Microgrid Topology Planning for Enhancing the Reliability of Active Distribution Networks. *IEEE Trans. Smart Grid* 9, 6, 6369–6377.

[12] Logenthiran, T., Srinivasan, D., and Wong, D. 2008. Multi-Agent Coordination for DER in MicroGrid. In *International Conference on E-Society, E-Education and E-Technology*.

[13] Bellifemine, F., Caire Giovanni, and Greenwood, D. 2007. Developing multi-agent systems with JADE. In *Wiley Series in Agent Technology*.

[14] Arefifar, S. A., Mohamed, Y. A.-R. I., and EL-Fouly, T. H. M. 2013. Optimum Microgrid Design for Enhancing Reliability and Supply-Security. *IEEE Trans. Smart Grid* 4, 3, 1567–1575.

[15] Rishab Arya, Rishabh Yadav, and Raghav Agarwal and O.V. Gnana Swathika. 2018. Dijkstra's Algorithm for Shortest Path Identification in Reconfigurable Microgrid. *Journal of Engineering and Applied Sciences*.

[16] Taha Selim Ustun, Cagil Ozansoy, and Aladin Zayegh. 2011. Implementation of Dijkstra's Algorithm in a Dynamic Microgrid for Relay Hierarchy Detection. In *IEEE SmartGridComm*.

[17] Bawayan, H. and Younis, M. 2020. Mitigating failure propagation in microgrids through topology reconfiguration. *Sustainable Energy, Grids and Networks* 23.

[18] Regener, V., Römmelt, G., Zeiselmair, A., Wasmeier, L., and Bogensperger, A. 2022. Design choices in peer‐to‐peer energy markets with active network management. *IET Smart Grid* 5, 4, 281–296.

[19] Kilthau, M., Karmann, A., Derksen, C., and Fay, A. 2023. *Metric for Analysing cooperative and competitive algorithms for distributed frequency control in microgrids*, CIRED 2023 - 27th International Conference on Electricity Distribution.

[20] Maddouri, M., Debbiche, A., Elkhorchani, H., and Grayaa, K. 2018. Game Theory and Hybrid Genetic Algorithm for Energy Management and Real Time Pricing in Smart Grid. In *2018 International Conference on Electrical Sciences and Technologies in Maghreb (CISTEM)*. IEEE, 1–6. DOI=10.1109/CISTEM.2018.8613383.

[21] Tofighi-Milani, M., Fattaheian-Dehkordi, S., Fotuhi-Firuzabad, M., and Lehtonen, M. 2022. Decentralized Active Power Management in Multi-Agent Distribution Systems Considering Congestion Issue. *IEEE Trans. Smart Grid* 13, 5, 3582–3593.

[22] International Renewable Energy Agency (IRENA). 2018. *Global Energy Transformation. A Roadmap to 2050*.

[23] Agora Energiewende. 2021. *Klimaneutrales Deutschland. In drei Schritten zu null Treibhausgasen bis 2050 über ein Zwischenziel von -65 % im Jahr 2030 als Teil des EU-Green-Deals*.

[24] Wagner, L. P., Reinpold, L. M., Kilthau, M., and Fay, A. 2023. A systematic review of modeling approaches for flexible energy resources. *Renewable and Sustainable Energy Reviews* 184, 113541.

[25] Derksen, C., Branki, C., and Unland, R. 2011. Agent. gui: A multi-agent based simulation framework. In *Proceesdings of the Federated Conference on Computer Science and Information Systems*, 623–630.