On the effects of communication topologies on the performance of distributed optimization heuristics in smart grids

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Abstract: Distributed heuristics have shown promising results in handling difficult optimization and coordination tasks in smart grids, which often have to deal with large numbers of components, distributed information and real time constraints. Some of these heuristics are distributed on an algorithmic level. This means that the way information is exchanged between the distributed units can effect the efficiency of the algorithm, in terms of computational effort, message volume, and convergence speed. It may even impact the effectiveness, i.e. the solution quality. The performance of control systems is of utmost importance for stable and optimal operation of critical infrastructure in smart grids. Therefore, factors influencing the effectiveness and efficiency, like the communication topology, must be thoroughly investigated in order to both initially configure them optimally and react appropriately to undesired behavior at runtime. The impact of the communication topology is studied with an experimental setup, using COHDA as an example heuristic. Systematic experiments are performed with various topologies and varying numbers of agents to illustrate the importance of a solid and maybe even dynamic choice of the communication topology for distributed heuristics in smart grid applications.

Keywords: Agent-Communication; Communication Topology; Exchange Topology; Multi-Agent Systems; Distributed Optimization; Network-based Distributed Algorithms; Smart Grid; COHDA

1 Motivation

The electrical energy system is currently in a process of profound change as a large proportion of conventional power plants is being replaced by renewable energy sources. This demands new approaches, such as decentralized control at device level, distributed coordination of energy sources, or real-time optimization at system level [Dö19].

Distributed control and optimization systems represent a way to handle the new scalability requirements arising from the large number of energy sources and the increased complexity caused by distributed information, increasing uncertainties and real-time requirements. In such distributed control and optimization systems, decentralized components take over control tasks at the local level, while the global system behavior emerges from the interaction

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of these components. Using multi-agent systems (MAS) is a natural way to implement such distributed systems [Be13]. For many practical problems the use of optimization heuristics, implemented by a MAS, has proven to be a useful approach, for example for scheduling problems of energy resources, e. g. in virtual power plants [Ni12], the optimal control of microgrids [Az17] and redispatch solutions [Ro15]

The application in the smart grid domain and thus the impact on critical infrastructure imposes specific requirements on distributed control and optimization systems and hence on the underlying algorithms, like *real-time performance* and *dependability* [AL12]. In the context of optimization heuristics, this implies reliable convergence into solutions of sufficient quality within a limited period of time. A crucial factor for the realization of these requirements is the way the communication between the distributed entities is handled. In [Ta09], Talbi identifies four design decisions that characterize the communication of distributed heuristics:

1. Exchange content (Which information is exchanged?)
2. Exchange criterion (When is the information exchanged?)
3. Integration policy (How is the information handled after the exchange?)
4. Exchange topology (Between which agents is the information exchanged?)

While the first three design decisions affect the character of the overall heuristic, the exchange topology can be varied without changing the basic nature of the distributed heuristic. When implementing a distributed heuristic though, decisions have to be taken to define the exchange topology. Therefore, the focus of the experimental study in this paper lies on the performance effects of different exchange topologies. The performance of the heuristic is defined as a combination of the quality of the achieved solutions (effectiveness) and the effort that was needed to achieve these results (efficiency).

In many smart grid use cases, such as the scheduling of energy resources for different purposes like aggregation for markets or redispatch scenarios, the agents only share limited amounts of information which improves privacy of data, measurements, cost functions and constraints [Mo17]. These characteristics, i.e. the distribution of information and the dependencies between the choices of different agents, lead to an even greater influence of communication on the efficiency and effectiveness of such heuristics. Therefore, the design of the communication aspects is an important prerequisite for a reliable behavior of the heuristic and thus the smart grid suitability of the MAS.

In this paper, we investigate the influence of the communication topology on this kind of heuristics, discuss possible pitfalls in the choice of communication topologies and thus motivate the need for a structured approach on the choice of the appropriate communication topology. The rest of this work is structured as follows: First we provide a short introduction to communication topologies for network-based distributed algorithms. We then present our approach to the experimental investigation of the effects of the communication topology, discuss the results and give an outlook on potential future work.

2 Communication topologies for network-based distributed algorithms

The communication topology can be considered as a graph in which each agent is represented by a node. The edges of the graph indicate whether agents can exchange information directly. Following this representation, an agent can only send messages to its nearest neighbors, i.e. those that have direct links in the graph [Le14] [OSFM07].
Communication topologies differ in certain properties, such as node degrees and the maximum diameter, meaning the number of edges adjacent to nodes and the longest distance between any two nodes. The differences in such parameters influence how information spreads in the system and how many messages are sent. It can also have an impact on the solution quality, as different communication topologies affect exploration and exploitation of the search space [Ta09].

During the design of distributed algorithms in the smart grid domain, often not much attention is paid to the communication topology. Sometimes the publications only mention that a topology exists, but do not describe it further, or explicitly state that it is out of scope. Sometimes, simply the topology of the physical communication infrastructure is used and sometimes that of the electrical network [Di18], [LSK11], [RS16].

However, there are several research areas dealing with the impact and design of topologies on dynamic systems on graphs. These include network science, which concerns the formation and function of networks in the real world, e.g. [St01], and many research topics in the field of networked control systems, which are closely linked to consensus problems, such as sensor fusion, synchronisation of coupled oscillators or formation control for multi-robot systems [OSFM07] [BH07]. Especially in the field of consensus algorithms, a considerable amount of research has been conducted on the effects and design of communication graphs, e.g. [OSFM07], [RBA05], [Le14]. Consensus algorithms as well as distributed heuristics can be used for the distributed solving of optimization problems. In both types of algorithms, information is repeatedly exchanged between neighbors, local decisions are made and then communicated between neighbors, to optimize a common goal. The main difference is, how the local adaptation of the selection of an agent is handled, either via a mathematical specification (consensus algorithms) or via a search in the local search space (heuristic). Therefore, in a heuristic, the calculations performed by individual agents can be much more extensive, such as executing a local meta-heuristic, machine learning or mathematical programming. However, the globally emerging system behaviour is similarly complex as that of consensus algorithms. Due to the parallels with distributed heuristics though, we assume that findings in the field of consensus algorithms can provide useful insights for communication topology research in distributed heuristics, and thus discuss the relevant state of the art in the following.

In [BH07], Baras and Hovareshti examine the effects of the communication topology on networked control systems in terms of convergence speed, cost of collaboration and robustness. Their investigations mainly concern consensus algorithms. In the first part of their work, they focus on the convergence rate as a function of the graph topology. The second largest eigenvalue (SLE) of the graph Laplacian (also algebraic connectivity or Fiedler eigenvalue) is an important factor that quantifies the convergence speed of consensus algorithms [OSFM07]. Baras and Hovareshti try to improve the connectivity of small world topologies by systematically adding links. In [Ca16], Cao et al. propose a distributed algorithm closely related to consensus algorithms for solving linear equations. Using both theoretical analysis and numerical simulations, Cao et al. show that topologies with shorter diameter, more homogeneous degree distribution or higher mean degree increase the convergence speed of their algorithm.

The work in this area is mostly focused on increasing the speed of convergence as a measure of performance. In the case of distributed heuristics, the solution quality must also be considered, since, in contrast to consensus algorithms, they only approximate the optimum.

3 Methodology

The aim of the experimental study is to show the influence of the exchange topology on the performance of distribute optimization heuristics. To achieve this, we use an exemplary algorithm that has been modified to make it more suitable for controlled setups, and conduct an intensive study of the effects of different topologies.

In this section we will first give an overview of the experimental setup, including the used topologies. We will then describe the exemplary algorithm (COHDA) and explain how and why the objective function and local optimization have been altered compared to the usual setup.

3.1 Experimental Setup

The experimental setup is used to investigate the following hypotheses:

1. The graph properties of the communication topology will affect the speed of convergence of a distributed heuristic similarly to that of a consensus algorithm
2. The graph properties will affect the solution quality of the heuristic
3. There will be a trade-off between solution quality and the cost of collaboration (communication traffic and calculation effort)

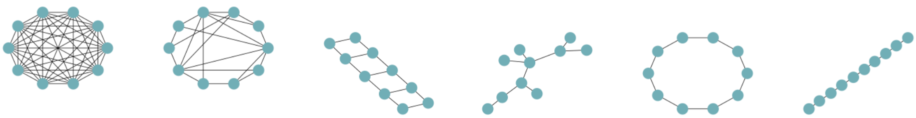
The agent system is tested with various communication topologies which are often used in literature such as complete graphs, ring-, tree-, small-world-, path-, and mesh- topologies.

Figure 1 shows these topology types for 10 agents. The topologies differ clearly in their graph properties, such as node degrees and the maximum diameter.

For the experimental setup, the number of agents is varied from small systems with five agents to systems with up to 200 agents. For each number of agents, each topology type is created with 5 different random seeds. To compare the differences in effectiveness, the solution quality, i. e. the value of the objective function, is used. To compare the differences in efficiency, the number of messages sent, the number of local search space executions performed, and the time required for convergence are considered. All experiments are performed on the same dedicated machine.

In addition, some restrictions have to be made in the experimental setup. No delayed communication is considered. The message volume is not explicitly considered since all messages have the same size for the same number of agents and thus the number of messages is an equivalent indicator.

Fig. 1: Overview of used communication topologies



(a) complete graph (b) small world topology (c) mesh (d) random tree (e) ring (f) path graph

3.2 Algorithm

COHDA is a 'combinatorial optimization heuristic for distributed agents' and was developed for the self-organized scheduling of distributed energy resources (DER) in virtual power plants (VPP) (for a detailed discussion see [HS17]). Each agent is responsible for the scheduling of one energy resource and knows the possible schedules and local preferences of its asset. A schedule represents an operational option of the DER, i. e. how much energy is being supplied or withdrawn at what time. The search space contains all possible schedules and can be further limited by operational constraints of the plants [BS13]. COHDA has been proven to always converge at least to a local optimum [HS17].

To investigate the impact of the communication topology, other influences in the experimental setup must be kept under full control [NTS14]. In the application setting of smart grid scheduling problems, the agents' search spaces consist of a set of feasible schedules, possibly extended by a decoder approach [HS17] [BS13]. As constructing such search spaces with defined properties regarding local minima for large scenarios is very difficult, an abstract and standard problem is chosen for analysis.

A suitable modified version of the algorithm is presented in [BL17]. Bremer et al. adapted COHDA to find the global minimum of a real valued objective function. An agent a_i is responsible for only one value x_i from a continuous search space. It performs its local optimization to minimize the global objective function, by adapting its own choice of x_i while considering the choices of other agents $x_j, j \neq i$ as temporarily fixed. This approach offers the advantage of simplifying the optimization problem itself, but allowing to choose an objective function that fulfills specific criteria in order to investigate differences in solution quality, i.e. convergence to local minima.

The chosen objective function is a variation of Schwefel's function 2.26 (see Equation 1), since is possesses several essential characteristics [Sc81]. As intended, it is continuous and each agent has to pick one value in the in the range of [-500, 500]. It can be scaled arbitrarily, which allows experiments with any number of agents. Furthermore, it is a multi-modal function which means that it has a high number of ambiguous peaks in the function landscape, i.e. it has many local minima [JY13]. Figure 2 shows a three-dimensional plot of the function. The function is separable, so each variable of the function can be optimized independently from the other variables. This is not the case for most practical problems in the smart grid and also makes the problem easier to solve. To change this property, an additional penalty function has been introduced (see Equation 2).

$$Schwefel_{2.26} : f(\vec{x}) = 418.9829n - \sum_{i=1}^{n} x_i \sin\sqrt{|x_i|} \tag{1}$$

$$Penalty : p(\vec{x}) = \left| \sum_{i=1}^{\frac{n}{2}} x_{2i} - \sum_{i=1}^{\frac{n}{2}} x_{2i-1} \right| \tag{2}$$

This penalty function is zero if the sum of all values selected by agents with even indices and the sum of all values selected by agents with odd indices is equal. The penalty is added to the value computed by the objective function (Equation 1). The goal of the optimization is to minimize the resulting Equation 3.

$$f'(\vec{x}) = f(\vec{x}) + p(\vec{x}) \tag{3}$$

The global optimum remains the same as for the unchanged Schwefel function. $f'(\vec{x})$ is zero if all agents choose $x_i = 420,968746$ for $i = 1, ..., n$. The introduction of the penalty function adds dependencies between the variables, making the objective function inseparable and thus making it harder to find the global optimum. Figure 3 shows the function landscape in a three-dimensional search space. For local optimization of this objective function the Simplicial Homology Global Optimization (SHGO) of [ESF18] is used, since preliminary tests showed fast convergence and excellent performance. Please note that the local optimization function is exchangeable within the limits of the convergence criteria of the algorithm that are fulfilled with choosing SHGO [HS17]. With this setup, we design an examination scenario that can be kept under full control as the properties of the objective function, and thus of the global and local solution spaces, are arbitrarily configurable, and in this case, were designed to be susceptible to convergence into local minima.

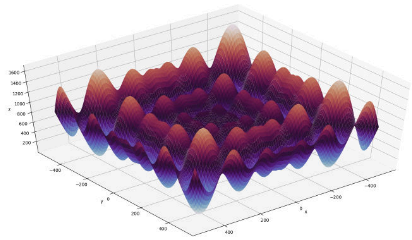


Fig. 2: Schwefel 2.26 for $n = 3$

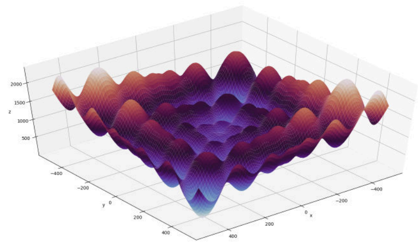


Fig. 3: Schwefel 2.26 with penalty for $n = 3$

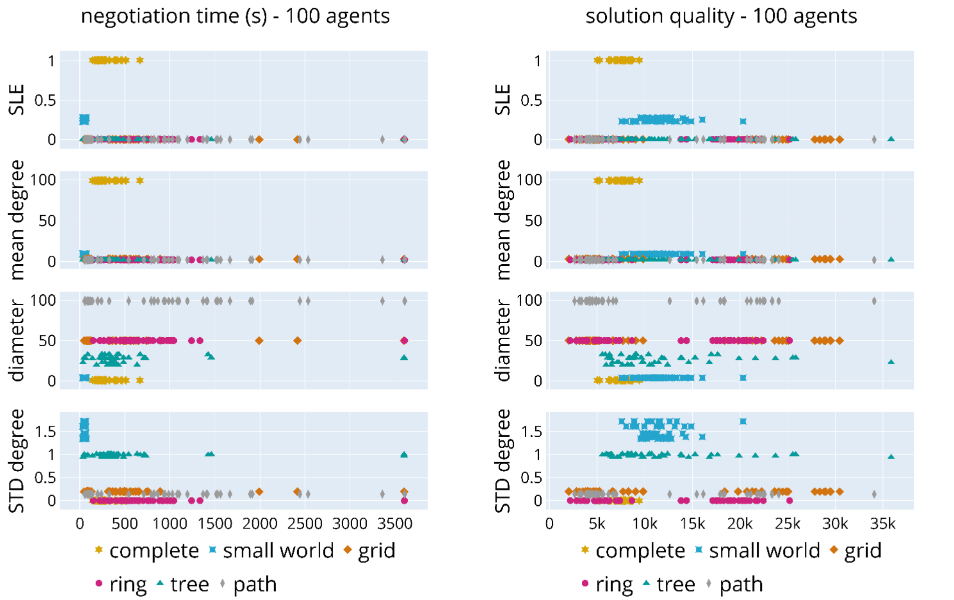
4 Results

To evaluate the previously established hypotheses, we will subsequently review the relevant data for each hypothesis. Thus, we first examine the effects of the relevant graph properties identified in [BH07] and [Ca16], namely SLE, diameter, mean degree and homogeneity of degree distribution, on convergence speed and solution quality (hypothesis 1 and 2). Afterwards we examine how the different topology types perform according to the different performance indicators, i.e. *solution quality*, *costs of collaboration (number of search space executions, number of messages)*, and *negotiation time* and investigate if the expected trade-off between the costs of collaboration and the solution quality exists.

As described in section 2, the communication topology of consensus algorithms has a significant impact on the speed of convergence. To show possible correlations, Figure 4a plots the *negotiation time* against each of the previously discussed graph properties for a MAS with 100 agents. It is apparent that a small diameter, a high mean degree and a large SLE have positive effects on the speed of convergence. The most prominent example for this is the complete graph. The topology with the second fastest convergence is the one with the second best values in these parameters, namely the small world topology. However, no correlation can be found for the STD of degree, since both heterogeneous and homogeneous topologies are associated with all grades of *negotiation time*. Therefore the assumption from hypothesis 1, that the mentioned graph properties also have a positive effect on the convergence speed of distributed algorithms, can be confirmed, with the exception of degree homogeneity.

Figure 4b shows the scatter plot for the four graph properties and the *solution quality*, again for a MAS with 100 agents. Since all graph property variations occur at each *solution quality* level, there appears to be no correlation. According to Talbi [Ta09], the characteristics of the topology make a difference in the degree of exploration and exploitation of the search space. This is reflected in the distribution of *solution quality*. The graph properties, which lead to fast convergence, also reliably result in a relatively good solution quality with low spread. Again, the complete graph and the small world topology are the most vivid examples for this. Ring, grid and tree graph, nearly reach the global optimum. These topologies have a medium diameter, low mean degree and also a rather low SLE. They differ in their degree

Fig. 4: Correlation of negotiation time and solution quality with graph properties - mean degree, standard deviation of the degree (STD degree) and the diameter.



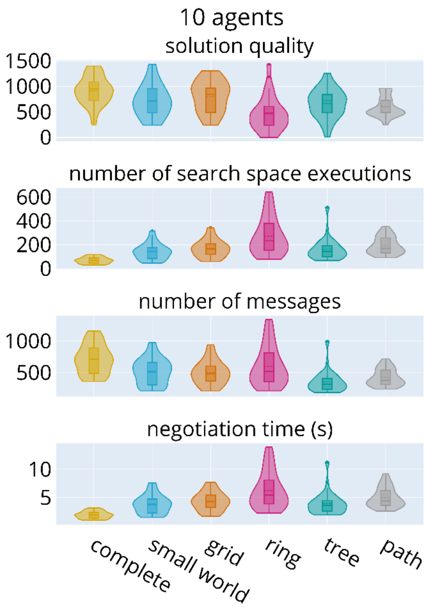
(a) Correlation of negotiation time with graph properties (b) Correlation of solution quality with graph properties

distribution as a ring is perfectly homogeneous and a tree one of the most heterogeneous topologies in the experiment. It can be assumed that this good *solution quality* is due to the fact that the negotiations coincidentally started at a favorable point and thus the topologies led to an extensive exploitation of a promising area of the search space.

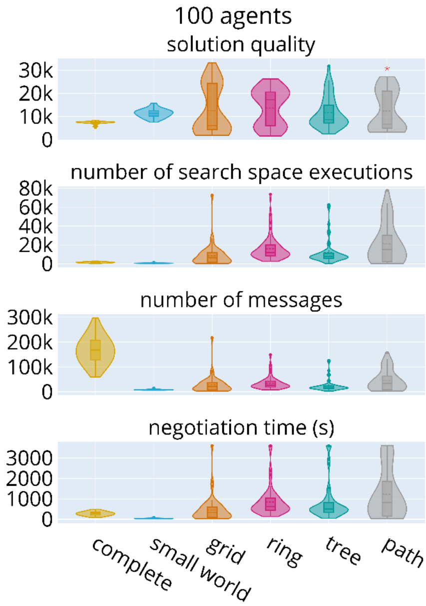
These results indicate that a high level of connectivity can lead to premature convergence and therefore poorer *solution quality*. Less connected topologies do not exhibit this problem and can therefore explore the search space more thoroughly. On the other hand, the exploitation is weaker and therefore they are highly sensitive to the starting point of the search. Hypothesis 2 states that the graph properties also affect the solution quality. This can be affirmed, although the graph properties do not directly impact how good or bad the quality of the solution is, but they do have an effect on how large the variation of the achieved quality and thus the reliability is.

The figures 5a and 5b show the performance of the topology types for a small MAS with 10 agents (5a) and a larger system with 100 agents (5b). These numbers are selected for presentation to show the typical behavior for smaller and larger MAS. Similar results were obtained in simulation runs with different numbers of agents. The figures show how the different topologies perform for all performance indicators and uses violin plots, which

Fig. 5: Extracts from the simulation results for 10 agents(left) and 100 agents (right) with 250 simulation runs per number of agents



(a) Results of the negotiation runs with 10 agents concerning the performance indicators as violin plots [HN98]



(b) Results of the negotiation runs with 100 agents concerning the performance indicators as violin plots [HN98]

show the distribution with an internal box plot surrounded by a density plot [HN98]. The depiction of the solution quality again underlines the results of hypothesis 2 and shows that the topology has an effect on the scattering of quality, especially with increasing system size. In relation to this, the diagram of the negotiation time represents the already explained correlation of the convergence speed with the same graph properties. The two middle rows contain the relevant parameters for collaboration costs (*number of messages*, *number of local search space executions*). The *number of search space executions* is not directly dependent on the communication topology here, since it is not triggered by the event of message arrival. Instead, each agent performs its tasks periodically. Yet it is still indirectly influenced through the total *negotiation time* and reflects the distribution of this indicator.

At first glance, the "*number of messages*"-indicator shows a similar distribution. However, regarding the MAS with 100 agents, it becomes clear that this similarity does not persist for the complete graph. The reason for this is the big difference in the graph properties (SLE, mean degree, degree distribution and diameter), which differentiates the complete graph more and more from the other topologies as the system size increases. It can thus be concluded that there is no clear trade-off between solution quality and collaboration costs with regard to hypothesis 3. Instead, there is a trade-off between reliable behavior with relatively good solution quality but with potentially high message volumes and unreliable behavior with an increased chance of finding the global optimum. In summary, the small world topology represents the best compromise among the tested topologies, since it achieves relatively good results in a reliable and fast way and with low collaboration costs. If the costs for message transmission are negligible, the complete graph is preferable.

5 Conclusion

Distributed optimization heuristics performed by MAS are a suitable approach to solve various tasks in smart grids, such as the coordination of large numbers of distributed energy resources. Some of these heuristics are distributed at the algorithmic level, making the communication of the agents itself part of the algorithm. With COHDA as a representative of this class of algorithms, the experimental study has shown that the communication topology has an influence on both solution quality and efficiency of such heuristics. The simulation results demonstrated that certain graph properties, such as mean degree, diameter and Fiedler eigenvalue, affect the convergence speed of distributed heuristics as has been shown for consensus algorithms. We presented results that give more insight into the effect of different communication topologies on the degree of exploration and exploitation of the search space. The key findings are:

- Highly meshed topologies converge reliably and quickly into relatively good local optima, though potentially involving greater communication effort. Moreover, such topologies encounter difficulties in escaping local optima and thus finding the global optimum.
- Sparsely meshed topologies have a higher probability of finding the global optimum through higher exploitation. However, they can also diverge completely and only find solutions of low quality. Such cases consume large amounts of resources, in terms of computing power and message volume and can lead to excessive negotiation times.

The use of heuristics operating critical infrastructures leads to the requirement to reliably obtain sufficient results in a limited period of time. The above findings indicate that there is no one-fits-all topology, and thus dynamic topologies might be advisable to weigh exploration and exploitation in an optimal way. In future work, we therefore address the question of how the topology can be intelligently changed during the negotiation period in order to achieve reliable and fast convergence with improved and maybe even guaranteed solution quality, while keeping the costs of cooperation low.

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