



Multi-Agent Systems for Resource Allocation and Scheduling in a Smart Grid

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Abstract

With the increasing integration of Distributed Energy Resources (DER) in the power grid, a decentralized approach becomes essential for scheduling and allocation of resources in a smart grid. Economic Dispatch (ED) and Unit Commitment (UC) are the two major resource allocation problems that play critical role in the safe and stable operation of a grid system. The uncertainty associated with renewable energy sources have made the resource allocation problems even more challenging for grid operators. The future grid will have a higher generation mix of renewable energy sources and a large load of Electrical vehicles, with the possibility of bi-directional power flow. This complex smart grid system necessitates the development of a decentralized approach to resource allocation problem, which allows inter-node communication and decision making. Multi-agent systems (MAS) is a promising platform to decentralize the traditional centralized resource allocation aspects of smart grid. This paper presents a comprehensive literature review on the application of MAS to Economic Dispatch (ED) and Unit Commitment (UC) in smart grids.

Keywords Multi-agent systems · Smart grid · Resource allocation and scheduling · Economic dispatch · Unit commitment

Introduction

The smart grid framework incorporates distributed generation, advanced communication network, smart meters and sensors to make the grid more reliable, flexible, adaptive and efficient. This new power system paradigm necessitates the need to revisit some of the traditional power system operations to meet the challenges of next-generation transmission and distribution systems [1]. Along with the integration of renewable energy sources, the deregulation in the energy market has created competition for power generation companies. Generation companies have an obligation to meet the customer energy demands even during peak hours and system outages. There is a need to properly allocate the generation sources to maximize the profit considering renewable generation and customer demand [2].

The presence of increased penetration of Renewable Energy Sources (RES) in the power system creates many technological challenges for the power companies owing to the need for improved system control to maintain the power quality to consumers [3]. The mix of conventional and RES must work in tandem to maintain the power generation at the required level. The process of committing the generators and allocating the required generation level has become a challenge to meet the increased demand, while using the generation from uncertain RES. These factors make the centralized control of a smart grid system complex and less efficient to process the diversity of data and controls [4]. The concept of Multi-Agent Systems (MAS) is put forward to solve this problem by using automated agent technology. The MAS converts a centralized control system into a distributed control model at a component level.

MAS is a collection of agents working together with each other to achieve an overall objective [5]. An agent can be defined as a computer system with the ability to take critical decisions based on the scenario to improve its objective [6, 7]. These software agents in a smart grid environment sense, communicate, collaborate and act with each other. The agents can act autonomously or semi-autonomously, with local or

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global information [8]. MAS technology is finding wide range of applications in the power system domain such as optimal power flow [9, 10], power system restoration [11–17], electricity market operation [18–21], power system control [22–26] and protection [27–29]. The focus of this paper will be restricted to the application of MAS in the fundamental resource allocation aspects of the power grid namely, Economic Dispatch (ED) and Unit Commitment (UC).

ED is one of the most important challenges in the power systems and it deals with the allocation of power generation among committed generators in order to meet the demand while lowering the generation cost [30]. Consumer demand for clean energy and government regulation has motivated the integration of Distributed Energy Resources (DERs) like solar photovoltaic, wind power, and fuel cells into the modern power grid. This makes ED a highly complex optimization problem which needs to consider the various factors like generator capacity, ramp-rate, failure rate, emission, load profile and generation from DER. Unit Commitment (UC) in a smart grid system is a highly complex optimization problem that schedules the startup and shutdown of generators to meet the demand while satisfying system constraints [31, 32]. The committed generators are modeled in the ED for generator scheduling. The smart grid systems which have significant DER and the increased interest from consumers to install RES have necessitated the need for a decentralized approach to commit and schedule generators. The increased uncertainty from RES has made ED and UC more complicated due to the intermittent nature of these power sources.

For understanding the application of MAS in resolving resource allocation and scheduling problems of smart grid, the paper is organized in five sections. Section II describes the architecture of a MAS in a smart grid system, section III and IV present comprehensive review on the application of MAS in ED and UC respectively, followed by conclusion in section V.

MAS for Smart Grid

An agent represents a computer system situated in an environment where it is capable of making decisions to achieve its design objectives. Moreover, an agent can be autonomous, social, reactive and proactive. Multi Agent Systems (MAS) are composed of agents interacting in a highly dynamic environment. These intelligent agents are being developed to have the functionalities on par with the human experts to act appropriately in the various scenarios that take place in a smart grid. The summary of various MAS architectures used for control of microgrid is summarized in Table 1 [33].

The centralized MAS architecture for micro grid control is discussed in the literature [34, 35]. The framework of distributed and three level hierarchical MAS for a smart grid is explained in P. Lu et al. [36] and K. E. Nygard et al. [37] respectively.

Most of the MAS based optimization problems rely on the technique of consensus algorithm to reach the solution. The main idea behind the consensus problem is to make a set of agents agree up on a certain value (usually a global function) by using local information exchange among agents (local interaction). This concept is utilized in different fields such as economics (Agreement problem), communication (Gossip algorithms [38]), statistical mechanics [39] (Synchronization) and robotics (Flocking [40]). It offers several advantages over traditional centralized methods such as distributed computation, computational efficiency, independent of graph topology and robustness to failure [41, 42]. In a consensus algorithm model, each node in the system is considered as a dynamic agent with a value or state associated with it. The value of the agent represents the decision variable with which it can reach consensus with other agents in the system. Researchers have explored different census methods for a microgrid system such as in the work by G. Hug et al. [43] where a combination of consensus and innovation method was utilized. A novel framework to model a full automation of a distributed smart grid system is presented in the work by K. E. Nygard et al. [37]. The model is based on the concept of an Intelligent Autonomous Distributed Power System (IDAPS), a microgrid with sufficient resources and intelligence to function autonomously within a global grid. A three-layer hierarchical system model with agents in higher level supervising the agents in lower levels is proposed. The model accomplishes modularity, scalability, and a balance between global and local decisions of agents. Distributed MAS based control offers several advantages such as autonomy, fault-tolerance low latency, efficiency and much more. It is a way of physically breaking complex control problems into smaller control problems, and then solving them closer to the control operation itself.

Development of Smart Grids will involve dealing with a big amount of data collected in a distributed manner. This data is communicated among equipment and devices to support decision-making process. Certainly, handling the amounts of data to be acquired and processed in such distributed systems to extract useful information bring its own challenges. Computational intelligence techniques are used to extract knowledge and overcome some of the challenges. In “intelligent” systems, data is pre-processed, processed, and then information is extracted for decision-making. Given the distributed nature of Smart Grids (SG), new advancements in distributed intelligence techniques spawned the MAS technique development. The following are some advantages and reasons to explore distributed MAS architectures over centralized architecture:

Table 1 Different MAS architectures for microgrid control [33]

MAS architecture	Type of agent	Role	Features
Centralized	Cognitive Agent	Higher level of intelligence/ communication capabilities	+ collects information at a single point
	Reactive Agent	Fast Response	+ capable of making global decision + flexibility and openness in the operation of smart grid – suffers from computational burden in case of large number of agents – single point of failure affects the entire system
Two-level hierarchical	High level agent	Infrastructure management, low level scheduling	+ distinct levels of decision making – failure of higher level agents results in critical conditions of the lower level agents
	Low level agent	Accept schedule from High level agent, asset management	
Three-level hierarchical	High level agent	Critical decisions, data and policy management	+ good scalability through delineation of roles to agents
	Middle level agent	Fault location, switching of grid connected/islanded mode	– failure of higher level agents results in critical conditions of the lower level agents
	Low level agent	Sensor management	
Distributed	Local Agent	Local information discovery/ communication	+ robust system with agents being capable of reorganizing and coping up with the loss of other agents

Advantages of Distributed MAS over centralized control:

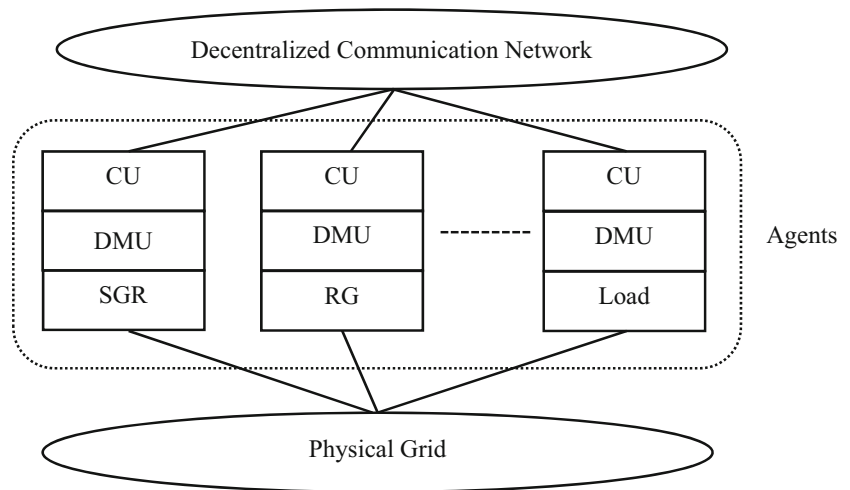
1. The SG components are often distributed and the energy management system is tightly associated with the communications between stakeholders and entities (agents) to exchange information, so MAS is an appropriate platform to develop distributed management functions.
2. SG is a holistic system and the failure of some part of it (e.g., the breakdown of a transmission line or cut down of a substation, transformer) should not affect the whole activities and operations, and hence fault tolerance can be easily attained in distributed architecture over centralized architecture.
3. SG should demonstrate the plug-and-play concept for integrating energy storage, loads, and sources at the building level with the external utility grid. Plug and play adaptability is widely proven by MAS. The nature of MAS enables it to scale up by adding other agents or by dispersing them in new environment with new resources and capacities. Hence, Distributed MAS building modules are highly scalable, and modular.
4. As SG will be composed of an aggregate of Micro grid, and hence the control can be delegated to micro grids. With futuristic smart grids being a simple collection of residential microgrids, each microgrid can exhibit distributed control.
5. One of the goals of the SG is to develop grid modernization technologies, tools, and techniques for Demand-

Response (DR) with the ability to dynamically optimize grid operations, resources and consumer participation. To do so, it is important to understand demand participation of consumers. As number of consumers are growing, it is essential to do the demand response analytics in a distributed fashion.

Due to the inherent advantages of distributed MAS architecture, it is well suited to resolve the complex ED problem of smart grid. A general framework for the implementation of MAS in smart grid (SG) system is shown in Fig. 1 [44]. SG system is an integration of the physical grid with the communication layer where the agents act as an interface. The communication layer is a strongly connected network with varying and configurable topologies. Each agent can be categorized into three units; namely Device Unit (DU), Decision Making Unit (DMU) and Communication Unit (CU). DUs can be considered as physical power system buses with components such as Synchronous Generators (SGR), Renewable Generators (RG), flexible load and rigid load. DMUs perform the local computing for the agents and CUs are the communication nodes, which transmit and receive information [45].

The internal structure of an agent model is shown in Fig. 2. An agent model consists of three units; Communication Unit (CU), Decision Making Unit (DMU) and Device Unit (DU). CUs are generally signal receivers/transmitters used to exchange information with neighbors. The calculator, sensors and controllers are part of DMU, which are responsible for the local computing in an agent. DMU is the brain of an agent node and capable of generating control instructions for the DU

Fig. 1 Framework for distributed multi-agent system for smart grid [44]



as well as responsible for communicating the information to the CU. DUs represent the traditional buses in a network which consists of different elements such as synchronous generators, Renewable Generators (RG), battery storage systems (BESSs), flexible and rigid loads. DU performs the control suggestions from DMU and also sends the feedback to the DMU.

There are number of simulation and open source tools available for modeling MAS platforms [46]. The most common ones are ZEUS, AgentBuilder, JADE, and MADKit. Features of these MAS modeling tools are listed in Table 2.

Economic Dispatch

Economic Dispatch (ED) is one of the fundamental problems in the power system domain. It is basically an optimization problem with the objective of reducing cost while maintaining the generation-load balance. ED schedules the committed

generators in the system to meet the demand. ED needs to conform to several other constraints for a safe and secure operation of the grid. The integration of uncertain renewable energy sources to the grid has made ED and power quality analysis more important and also more complicated [52, 53].

Distributed algorithms are becoming popular for intelligent decision-making and control and these algorithms appear to be promising in the context of smart grid. These algorithms are robust, immune to topological variations and can support the “plug-and-play” feature of the future grid. However, it is more challenging to include the operational constraints in such a distributed formulation. Many researchers have proposed a consensus-based approach for ED without losses and lower and upper power boundaries. A consensus algorithm is widely used in solving the ED problem in smart grid. It is a method used to achieve agreement on a single data value among distributed systems. This algorithm is designed to achieve reliability in a network involving multiple unreliable nodes. [36, 54–56].

Fig. 2 Internal structure of an agent [44]

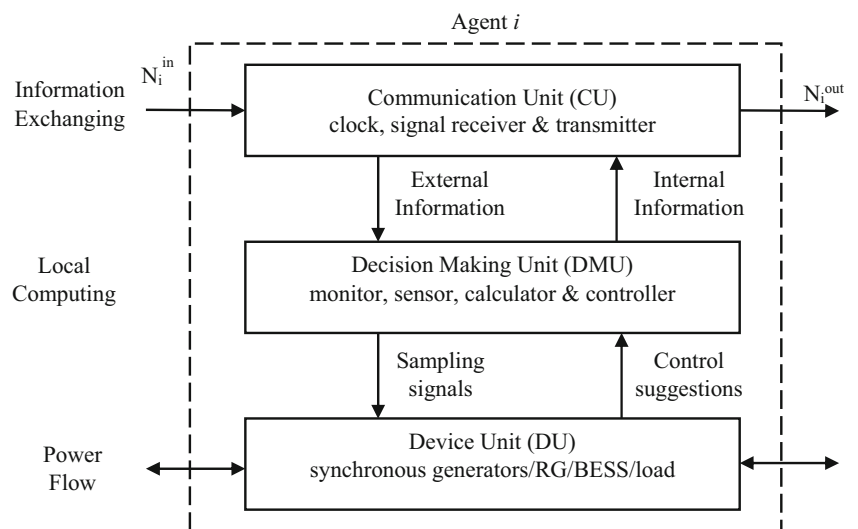


Table 2 MAS modeling tools

MAS tools	Description
ZEUS	ZEUS [47] is a multi-agent platform developed by the research program of British Telecom intelligent system research laboratory. ZEUS allows the design of multi-agent distributed systems. This platform, developed in Java, automatically generates Java code from the agents specified graphically.
Agent Builder	Developed by Reticular Systems Inc., AgentBuilder [47], it is based on BDI (Believe - Desire - Intention) models Agent [48] and AGENT-O language [49]. It is remarkable for the quality of its software and a good academic model. AgentBuilder is a commercial design software for “intelligent” agents i.e., cognitive and collaborative agents. AgentBuilder consists of two main components: the toolkit and runtime system.
JADE	JADE [50] is a multi-agent (multi-host) platform developed by Bellifemine. F., Pogy. A., Rimassa. G. and P. Turci by Telecom Italia Lab “Tilab formerly CSELT” in 1999. This platform aims to simplify the construction of interoperable MAS, achieve compliant applications with the standard FIP A97 (Foundation for Intelligent Physical Agents) to facilitate the communication of JADE agents with non-JADE agents, and optimize the performance of a distributed system agent. JADE includes all accredited component that manages the platform: Agent Communication Channel (ACC), Agent Management System (AMS), and Director Facilitator (DF).
MADKit	MADKit [51] is a platform for MAS developed by Olivier Gutknecht and Jacques Ferber in Laboratory of Computer Science and Robotics and Microelectronics of Montpellier. MADKit was motivated by the need for a more flexible platform possible, and able to adapt to different agent models and application areas. MADKit is a modular multi-agent platform and scalable, written in the Java language. It allows the creation of MAS based on the relational model Aalaadin or AGR (Agent / Group / Role): agents are located in groups and play roles. MADKit takes advantage of object-oriented programming: MADKit features are contained in the MADKit kernel.

In a conventional centralized method (e.g. Lagrange multiplier method), at the optimal point, all the generators will have the same incremental cost. An appropriate consensus algorithm can guarantee a similar result by having all the consensus variables to converge to a common value asymptotically. Based on this concept, Z. Zhang and M. Chow [57] introduced an Incremental Consensus Algorithm (ICC) to decentralize the ED problem by choosing incremental cost (IC) as a consensus variable. The model consists of a local controller (generation unit) which will update its consensus variable depending up on the neighbor’s values. The proposed approach requires a leader node, which will decide whether to increase or decrease the IC based on the demand constraints. The authors tested the approach on a 3 unit and 5 unit system to test the validity and convergence of the proposed approach. They showed a successful implementation of consensus algorithm in ED but lacked a fully distributed model since it needed a leader node to control the agents. A more detailed description about ICC is provided in [58].

The previous paper utilized ICC algorithm to implement ED in a distributed fashion but relied on a leader-follower consensus algorithm. A leader node needs to be selected, which will gather the local power mismatch from the follower nodes to calculate the total power mismatch. The follower nodes need to report their power mismatch to their leader. Z. Zhang et al. [59] introduced a two-level consensus approach

to acquire system power mismatch. This new approach will eliminate the need for a single leader node to do all the calculation. An average consensus will run at the lower level of the two-level method and ICC will be employed at the second level to process the mismatch information. This is an improved version from the method proposed in [57]. It is more distributed and does not require a fixed communication network.

A decentralized approach to ED in a microgrid with Distributed Generators (DG) was explored by N. Cai et al. [7] using a MAS. Here, each DG was assumed to have an agent which could receive local information and communicate only with its nearest neighbors. Agents compete with others to obtain a local solution, thereby obtaining a global optimum. The authors used the concept of consensus among agents to obtain the optimum solution for the ED. The authors validated the approach on five and fifty agent systems but did not compare the results with a centralized approach.

A consensus control based approach to solve the ED problem in a smart grid was developed by S. Yang et al. [60]. The approach solves the ED in a distributed fashion with the generators acting collectively to receive the mismatch between demand and power generation information, which is the feedback for the agents. The total mismatch is generated in a collective fashion from the estimate of local mismatch by the agents, which removes the need for a leader agent to collect

the global information. The incremental cost of the generators is chosen as the consensus variable and incremental cost criterion was used to obtain the optimal dispatch. The method was found to have the same precision as the Lambda-Iteration approach, a centralized method, with less communication overhead.

A distributed ED model considering line loss was developed by G. Benetti et al. [61]. The nodes in the model run two consensus methods in parallel; one to find the Lagrangian variable and a second one to find the power mismatch. The first method is a first-order consensus algorithm which uses a proportional controller to bring the power mismatch to zero and to satisfy the generation-demand equality constraint. The second consensus method uses the work allocation concept to find the power mismatch. The authors assert that the proposed method can satisfy generation constraint and can handle line loss in the system. The comparison between the distributed approach and the centralized approach to verify its convergence speed and accuracy was not attempted by the authors.

A. Cherukuri et al. [62] explored the concept of distributed consensus-based approach to model an ED which can handle changing load conditions and can remain stable under intermittent power sources. The proposed model employs two dynamical systems namely, dynamic average consensus and Laplacian non-smooth gradient. The mismatch between generation and load is estimated in a distributed fashion by the consensus method and the Laplacian non-smooth gradient dynamically allocates the generation. The approach can reach optimum solution from any initial power allocation and does not require a feasible allocation as the initial value. The authors verified the effectiveness of the method to handle dynamic loads and intermittent power sources.

K. Luo et al. [63] developed a MAS based distributed ED model for an electrical grid system with RES, which can be deployed for real-time applications. The proposed approach is a two-step process, with the first step calculating the initial generation values using adjacency average allocation algorithm and the second stage performs the ED in a distributed manner using local replicator dynamics. The first stage handles the equality constraints in the model while the second stage conforms to the inequality constraints. They validated the effectiveness of the proposed method but did not compare the performance of the method with similar approaches.

A distributed ED model for an islanded microgrid system was developed by P.P. Vergara et al. in [64]. The model considered both active and reactive power in the optimization model. The primal-dual constrained optimization method was used to solve the problem in a distributed fashion, in which two consensus methods are executed in parallel to obtain the dual values or incremental costs. The authors validated the performance of the proposed method by comparing to a classical Lambda method and also the capability of the method for fault tolerance.

F. Guo et al. [65] explored the potential of a distributed ED model for a smart grid system with random wind power. The proposed model works on the projected gradient and Finite-time Average Consensus Algorithm (FACA) and supports the plug-and-play feature of new generation smart grids. The random wind power generation is modeled using the deterministic method with overestimation and underestimation cost variables. The agents can choose arbitrary initial values and are not required to share gradient or incremental cost information with the neighbors. The authors validated the effectiveness and performance of the proposed method on IEEE test systems.

A consensus-based distributed ED taking into account generator dynamics was studied by J. Cao et al. in [66]. The authors used comprehensive generator constraints to improve the consensus algorithm and analyzed the effect of different communication topologies on the speed of the consensus algorithm. The model relies on local power mismatch data from the agents rather than a leader node to collect global information. The authors asserted the superiority of the proposed method by comparing with Lambda iteration and PSO methods. The generator dynamics was found having a significant effect on the speed of the consensus method while the effect of communication topology was not significant.

A distributed consensus-based approach to solve ED in a microgrid was developed by Z. Yang et al. [67]. They used a novel concept of virtual incremental cost as the consensus variable which does not require the nodes to share power output or generator parameters. The algorithm has the advantage of not depending on the local power mismatch to reach the optimum and maintaining the supply-demand balance even during transients. They reported reduction in communicational burden between nodes and improved reliability of the algorithm.

Y. Li et al. [68] developed a distributed ED model for a combined heat and power system. The MAS based framework utilized two consensus protocols, one optimizes the electrical incremental cost function while the other gets a common value for the heat incremental cost. The heat and power coupling in the objective function and constraints are managed by these two consensus variables. It works in a completely distributed fashion without the need for a leader agent with the global information. They report the effectiveness of the proposed ED model by comparing to a centralized approach using Lagrangian relaxation method.

Z. Yang et al. [69] proposed a distributed consensus-based model for the ED in a smart grid system which maintains the supply-demand balance even during the transient process. The method has the advantage of not relying on the supply-demand mismatch and hence can be used online. The proposed method does not require a leader node with the complete information of power demand in the grid system. It uses the maximum incremental cost of the neighboring generators and developed a

method to increase or decrease the incremental cost of a saturated generator to maintain the supply-demand balance during iterations. H. Xing et al. [70] utilized an average consensus based bisection approach to perform distributed ED. The method has the advantage of not relying on prior information or a leader node to perform the optimization.

G. Binetti et al. [71] developed a distributed model to solve non-convex ED problems. The non-convexity comes from the valve-point effect, prohibited operating zones, multiple fuel option and transmission losses but makes the model more realistic for real-time operations. The proposed model is fully decentralized and does not require a leader node with the global information. The method has the added advantage of being deterministic while heuristic methods do not guarantee the uniqueness of the solution from a single run. A combination of auction mechanism and market-based MAS was used to design the distributed ED and the authors tested the validity of the method on standard test systems. G. Binetti et al. [72] also proposed a distributed ED model which considered transmission losses in the system using a combination of two consensus algorithms running in parallel. The model utilized a first order consensus protocol to calculate the local power mismatch to satisfy the demand constraint and a second consensus algorithm to calculate the system power mismatch.

A transition of the MAS based distributed ED from laboratory set up to industrial model is studied by G. Zhabelova et al. [73]. An incremental cost consensus approach model based on the industrial standard IEC 61499 is used to solve ED in a smart grid environment. IEC 61499 is a promising industrial standard used as an architecture for the development of distributed systems in control and automation. The agent-based system modeled after the IEC 61499 standard will be suited for industry application and can be executable on the target platforms. The authors tested the proposed model on a 5-node system with industrial controllers.

A combination of MAS and Particle Swarm Optimization (PSO) called MAPSO (Multi-Agent Particle Swarm Optimization) was proposed by C. Wu et al. [74] and was applied to the ED problem. The proposed method overcomes the shortcomings of PSO, the fast convergence to the local optima, and achieves high convergence speed and precision. The agents are modeled to have the ability of self-learning to improve the problem-solving ability. The authors verified the effectiveness of the proposed method on IEEE test buses and the method was found to be faster than evolutionary algorithms. A hybrid of MAS with PSO, deterministic search and bee decision-making process called HMAPSO (Hybrid Multi-Agent based Particle Swarm Optimization) was proposed by R. Kumar et al. [75]. The HMAPSO method was applied to an ED model with valve-point effect and was observed to be more robust and accurate than other PSO methods.

A dynamic agent-based approach to model a decentralized ED was developed by V. Loia et al. [76]. ED was solved using self-organizing dynamic agents equipped with distributed consensus method. C. Zhao et al. [77] explored the effect of cyber-attacks on a consensus-based ED model. The authors tested the performance of the algorithm for false data injection into the broadcast information, offline and online ED models, and bounded and unbounded generation cases.

The increased amount of communication between nodes in a smart grid system can lead to communication bottlenecks which can cause convergence issues in consensus-based ED models. C. Li et al. [78] developed an event triggered consensus-based ED model to reduce the communication overhead in a smart grid system. The authors reformulated the ED model using θ -logarithmic barrier to conduct the information exchange in a distributed fashion. The reformulated ED model is solved in a two-stage process; the initial values for the agents are generated using connected dominating set based distribution algorithm as the first stage and in the next stage a consensus-based optimization is applied to the system. The authors stated that asynchronous communication-based event triggered ED model can significantly reduce the communication exchange in a smart grid system, but the event triggered mechanisms can have a negative impact on the convergence rate. A fast gradient-based method is used to accelerate the convergence rate in the optimization model.

Most of the papers discussed above assume a perfect communication between agents without any information loss, but in a realistic smart grid environment can have packet loss and communication failures. Y. Zhang et al. [79] proposed a distributed ED model which remains robust under information loss among agents. A combination of two algorithms running in parallel, Robust distributed system Incremental Cost Estimation (RICE) algorithm, was introduced by authors to handle the issue. The model contains a Gossip algorithm to find the power mismatch estimation and consensus algorithm for the incremental cost estimation. They report that their method outperforms the consensus method to packet loss and delivered good results even with a 5% information loss in the network. Another study on distributed ED under communication uncertainties is by G. Wen et al. [80]. The proposed approach utilized a robust consensus model to counter the communication uncertainties. A study of consensus-based ED model under dynamic communication network is evaluated by M. Hamdi et al. in [81]. T. Yang et al. [82] explored a distributed ED model for a system with potentially time-varying topologies and network delays. The authors proposed a gradient push-sum based method to handle the network challenges.

The application of distributed ED using consensus theory in a microgrid is by proposed R. Wang et al. [83]. The proposed method is a fully distributed approach without a leader or a virtual control node. The incremental cost of

each bus in the system is taken as the consensus variable. The authors validated the performance and convergence of the distributed ED in a microgrid model. A similar approach for distributed ED in an islanded microgrid is proposed by Z. Tang et al. [84] by using IC as the consensus variable. A distributed power dispatch model for a multi-microgrid scenario is reported by X. He et al. [85] utilizing a primal-dual consensus algorithm. They evaluated the performance of the proposed algorithm on an IEEE 30, 57 and 300 bus systems. A study on distributed control architecture for a hybrid AC/DC microgrid is performed by P. Lin et al. in [86]. In most of the above cited papers for ED, an evaluation of generation cost is not performed for the different approaches and moreover the problem of ED is not solved in a more realistic manner with non-negligible losses. Limited work has been done on the implementation cost of these approaches in a smart grid system. A summary of the above cited papers and their features are listed in Table 3.

Unit Commitment

Unit Commitment is the process of determining the schedule of generating units within a power system. The optimized schedule is generated subject to device and operating constraints of the system with the objective of minimizing the cost for utilities [92]. The ED optimization is usually performed on the committed generators from the UC step. Various approaches were used to find the optimal schedule from the UC problem ranging from highly complex and theoretical methods to simple rule of thumb methods [93–97]. The scope of the UC problem depends on the generation mix, operating and security constraints set by the utility. The focus of this review is on the decentralized approaches which utilized MAS to solve UC problem.

Authors in [87] developed a centralized approach to solve UC in a smart grid system using a MAS based architecture. The agents communicate information to neighboring agents, but the UC happens in a centralized controller. Figure 3 shows the different agents in a centralized UC. The proposed method helps to reduce the communication overhead but has the demerits of a centralized controller such as a single point of failure, increased computation time with complexity, unavailability of plug-and-play functionality etc.

A distributed UC model based on MAS was developed by T. Nagata et al. [31, 98]. The proposed model consists of three types of agents namely Generator Agents (GA), mobile agents (DA, UA) and Facilitator Agent (FA). The FA contains the objective function. The system level constraints are satisfied by the interaction between GA and mobile agents and the GA handles the local constraints. The two mobile agents are provided to improve the

communication in the system. The decrease mobile agent (DA) are intended to reduce the generated output and increase mobile agents (UA) initiates an increase in generated output. In the proposed approach, mobile agents travel throughout the system and negotiates with the generator agents, depending up on the operating conditions. The performance comparison of the method with dynamic programming yielded similar results but it is not a fully decentralized method since it has a leader and mobile nodes as an interface between generator agents. Figure 4 shows the architecture of the proposed method.

An improved version of the method proposed in [31] was presented by J. Yu et al. in [88]. The proposed MAS agents are more intelligent and have the capability to solve complex optimization problems. The profit maximization objective is obtained using three types of agents, namely central agent, mobile agent and generator agent. The central operator in the system is the central agent which commands the mobile agents to achieve the objective function. The mobile agents travel to each generator to negotiate and reach a satisfactory result. The model is not fully decentralized as there is an agent acting as a central controller. The authors validated the proposed model against a hybrid Lagrange Relaxation - Evolutionary Programming (LR - EP) method.

A MAS based UC model for a smart grid system considering RES uncertainty was developed by X. Zhang et al. [89]. The model considered the uncertainty associated with wind, solar and load along with the charging and discharging of PHEVs (plug-in hybrid electric vehicles). The hierarchical system consisted of management agents, work agents, cooperative co-evolution agent and object cooperative agent. The work agents used adaptive GA to solve the optimization.

A MAS based approach to solve the profit based UC problem was explored by J. Yu et al. [99]. Rule-based, and dynamic programming methods were used to solve the profit based UC. D. Sharma et al. [91] introduced an improved version for the profit based UC. The ISO agents in the proposed method used a rule-based intelligence to work in conjunction with generator agents to maximize the objective function. The functionality of generator agents is limited to maximize their profit for a given demand and reserve using real – parametric Genetic Algorithm and to share the information with the ISO agents. The maximum profit generating agents are committed to the system by ISO agents while satisfying the up/down time constraints. The authors reported the performance of the proposed method with several hybrid methods.

T. Logenthiran et al. [2] utilized MAS concept to develop a resource scheduling model for an islanded power grid with integrated microgrids and DER. The proposed methodology has three stages; microgrid scheduling to

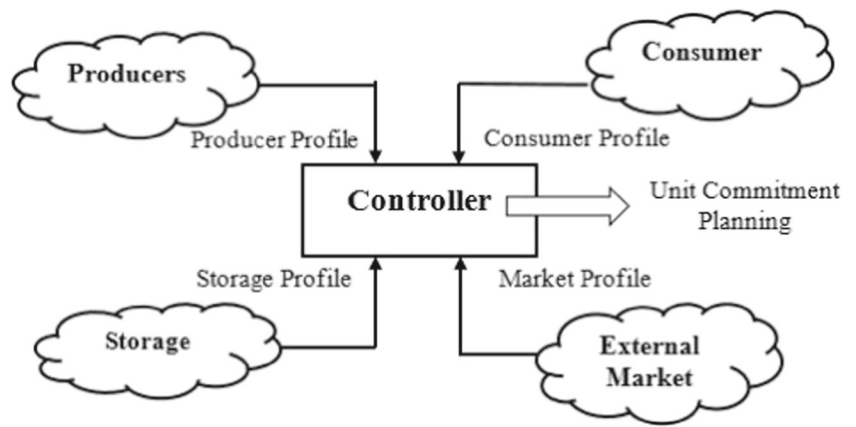
Table 3 High-level systematic summary of MAS application in ED and UC

Problem/ Architecture	Algorithm	Platform	Constraints	Implementation	Author, Year	Remarks
ED/Distributed	Incremental Cost Consensus (ICC)	–	Demand Constraint	Simulation on 3 unit and 5 unit system	Z. Zhang et al. [57] 2011	+ Successful implementation of consensus algorithm in ED - Leader node need to be selected + Not a leader-follower structure + Computation more distributed
	Average consensus + ICC	–	Demand, Generator constraints	Simulation on a 5 unit system	Z. Zhang et al. [59] 2011	
	Consensus based	–	Demand, Generator constraints	5 generators in a prototype microgrid	N. Cai et al. [7] 2012	+ utilized Local information among agents + proposed an improved communication algorithm for the agents + utilized mismatch between demand and power generation
	Consensus based	MATLAB	Demand, Generator constraints	Simulation on IEEE 14 bus system	S. Yang et al. [60] 2013	+ same precision as the centralized method (Lambda-Iteration approach) + Developed an industrial model for the MAS based ED
	Incremental Cost Consensus (ICC)	MATLAB	Demand Constraint	5 Node system (IEC 61499 Architecture)	G. Zhabelova et al. [73] 2013	+ used industrial standard IEC 61499 + used two consensus algorithms in parallel
	Consensus based-parallel	MATLAB	Demand, generation, Transmission loss constraints	Simulation on IEEE 6 and 300 bus system	G. Benetti et al. [61] 2014	+ communication network has the same topology of the power system + improved distributed coordination algorithm
	Dynamic average Consensus	–	Power and Generator constraints	15- Bus System	A. Cherukuri et al. [62] 2014	+ can handle intermittent energy sources, dynamic load conditions + considered generator dynamics + compared different communication topologies
	Consensus based	MATLAB/Simulink	Generator, ramp-rate limit, line-flow limit constraints	Simulation of a five-generator smart grid model	J. Cao et al. [66] 2014	+ ability to solve non-convex ED problems +Utilizes a leaderless consensus protocol
	Distributed auction-based algorithm	MATLAB	Valve point effect, multiple fuel options and prohibited operating zones	Simulation on 10, 15 and 40 generators	G. Binetti et al. [71] 2014	+More robust & Fault tolerant + self-organizing dynamic agents + A prototype version of the self-organizing architecture is developed
	Distributed average consensus	DICE /MATLAB	Demand, Generator limits	Simulation on IEEE 118 and 300 bus system	V. Loia et al. [76] 2014	+ can be deployed for real-time applications + Fully distributed computation + utilized game-theory concepts
	Distributed replicator dynamics	JADE	Demand, Generator constraints	Simulation on system with 3 DGs and 3 loads	K. Luo et al. [63] 2015	+ used a combination of MAS and Particle Swarm Optimization + faster than evolutionary algorithms
	Multi-Agent PSO	MATLAB	Demand, Generator constraints, Valve-point effect	Simulation on IEEE 3, 13 and 40 units	C. Wu et al. [74] 2015	+ considered random wind power generation + Incremental cost of generators not required
	Projected Gradient and Finite time average consensus	–	Demand, Generator constraints	Simulation on 6 bus and IEEE 30 bus system	F. Guo et al. [65] 2016	

Table 3 (continued)

Problem/ Architecture	Algorithm	Platform	Constraints	Implementation	Author, Year	Remarks
Consensus based	-	-	Demand, Generator constraints	Simulation on a Five-unit system	Z. Yang et al. [67] 2016	+ Plug-and-Play property + virtual incremental cost as the consensus variable + maintains the supply-demand balance during transients.
Consensus based- two protocols	-	-	Electrical and heat power balance constraints, capacity limits	Simulation on 16 Bus test system	Y. Li et al. [68] 2016	+ modeled ED for a combined heat and power system
Consensus based	-	-	Demand, Generator constraints	Simulation on IEEE 57 Bus system	C. Li et al. [78] 2016	+ No leader or central controller + event triggered consensus-based ED model + reduces the communication burden in the network
Robust distributed system incremental cost estimation (RICE)	-	-	Demand, Generator constraints	Simulation on IEEE 9 Bus system	Y. Zhang et al. [79] 2016	+ combination of two algorithms running in parallel + can remain robust under information loss
Consensus based- two in parallel	-	-	active and reactive power balance constraints	Simulation on IEEE 30 Bus system	PP. Vergara et al. [64] 2017	+ considered both active and reactive power in the model + based on primal-dual constrained decomposition
Consensus based	-	-	Demand, Generator constraints	Simulation on IEEE 14, 118 Bus systems	Z. Yang et al. [69] 2017	+ Does not rely on the supply-demand mismatch
Consensus based	-	-	Demand, Generator constraints	Simulation on 10 bus and IEEE 118 bus system	R. Wang et al. [83] 2018	+ Can be used in real-time applications + Implemented distributed ED in a microgrid
UC/ Centralized	Centralized decision-making algorithm	JADE	Demand, renewable, storage constraints	Energy transport network in France (RTE)	S. Hajjar et al. [87] 2015	+ Considered bus power + Energy storage considered + reduced communication overhead
UC/Hierarchical	Simple negotiation strategies	Java	Demand, Reserve, Ramp-limit constraints	Simulation on 10 unit system	T. Nagata et al. [31] 2002	+ obtained results close to dynamic programming
UC/ Distributed	dynamic programming and rule-based method	Java	Power and reserve limit, system constraints	Simulation on 10 unit system	J. Yu et al. [88] 2005	+ agents can solve complex optimization problems
	Cooperative co-evolution algorithm	Mathematica	PHEV limit, Generation constraints, Ramp rate limits	10-unit system with standard input data of power plants	X. Zhang et al. [89] 2016	+ considered uncertainty associated with wind, solar and load + Considered PHEVs
UC/ Distributed	Zonal optimization approach	MATLAB	Demand constraints	Realistic grid with two distributed energy sources	E. Kaegei et al. [90] 2008	+ Two-stage optimization model + There is no leader node in the model
	Real-parametric genetic algorithm (GA)	JADE	Demand, ramp limit, reserve constraints	Simulation on a 10 unit system	D. Sharma et al. [91] 2011	+ utilized genetic algorithm to solve the optimization problem + Rule based intelligence added to ISO agents

Fig. 3 Smart grid communicating agents in a centralized UC [87]



satisfy its internal demand as the first step, the second stage being contacting the network to analyze the possibility of exporting power, and the final step is to schedule the whole microgrid considering both internal demand and the power transfer from the second stage. The authors used the JADE platform to simulate the MAS system and used Lagrangian Relaxation with Genetic Algorithm to schedule the microgrid resources internally. They report the robustness and scalability of the method by testing it in a PoolCo energy market.

E. Kaegi et al. [90] proposed a decentralized approach to solve the UC problem using the MAS concept. The methodology was based on zonal approach consisting of generator agents, load agents and zone agents. The generator agents (GA) and load agents (LA) handle the local profit maximization within a zone while the zone agent handles the interaction with other zones. The zone agents have no financial objectives but only acts as a service agent for the entities within its zone. The optimization is done in two stages. The intra zone level is the competition between agents within a

zone to reach the profit maximization. In the next stage, the optimization happens during the interaction between zones. The paper only focused on the intra zonal activities, but the inter-zonal activities also play a significant role in profit maximization. Figure 5 represents the zonal approach used by the authors. A summary of the work done by different researchers on ED and UC problem which utilized MAS concepts are summarized in the Table 3.

Conclusion

This paper presented a literature review on the application of MAS for ED and UC in a smart grid. The integration of DERs into a grid requires a decentralized control strategy to incorporate these resources and to maintain the grid resiliency. The multi-agent technology is a promising and scalable platform to implement distributed resource scheduling and allocation using various computational techniques.

Fig. 4 MAS based UC model [31]

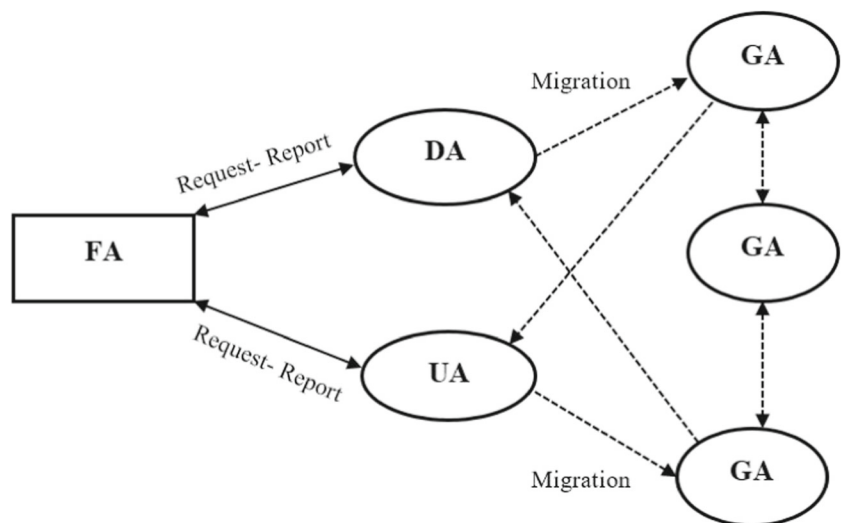
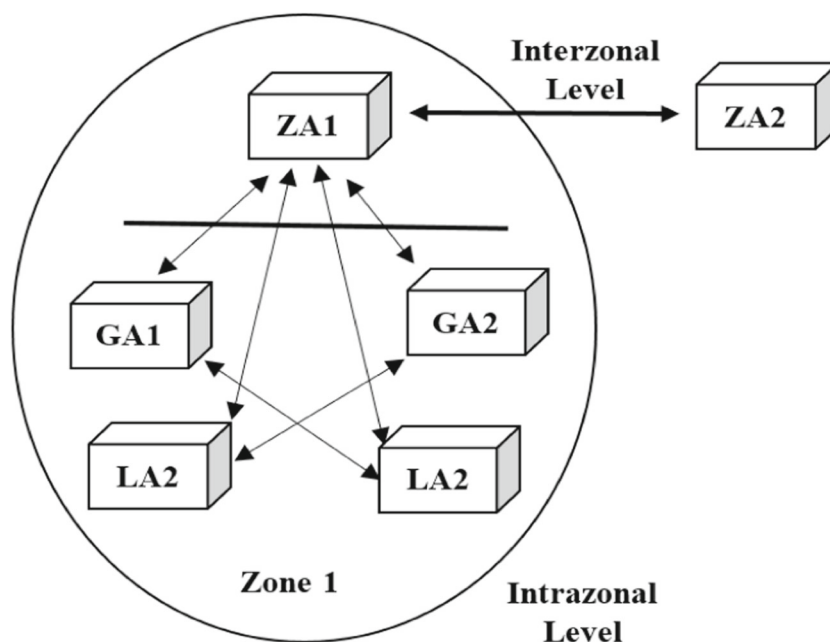


Fig. 5 Agent hierarchy in the UC Model [90]



Though there are many centralized algorithms being used to solve the ED problem, a small change in the smart grid may lead to redesign of these centralized approaches. Thus, there is a need for a distributed ED approach which can enjoy the benefit of robustness, scalability and less information requirement. Different distributed algorithms for solving ED problem have been proposed by many researchers in the literature. Of all these distributed approaches, consensus-based algorithm has evolved as the promising computing method for solving ED. The consensus-based ED algorithm can make the analysis tractable by simplifying the system into linear for the iteration process. Most of the consensus-based algorithms available in the literature are useful in solving only convex ED problem without transmission losses. On the other hand, an auction-based algorithm has been proposed to solve nonconvex ED problem. However, most of the investigations reported in the literature are limited to implementation in the simulation environment without addressing the challenges of different scenarios of a smart grid in real time. Hence, these approaches have to be established in real time which would be helpful in solving ED problem in a smart grid.

Researchers have explored the application of MAS in centralized, hierarchical and distributed models for an UC problem. Most recent works focused on a distributed model utilizing concepts from the negotiation strategies and genetic algorithm. The distributed UC models used a zonal approach consisting of controller/zonal agents facilitating the communication among agents and these models are not completely distributed. There is a need for a completely distributed UC

model which considers the increased DER penetration into the future grid. Most of the reviewed articles focused on the implementation and convergence ability of the proposed methods, more work needs to be done on evaluating these methods for their speed and cost savings in a real-time environment.

We believe that this paper can act as a resource for researchers in academia and analysts in utilities to understand the background on MAS's application for smart grid management and control.

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