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## RESEARCH ARTICLE

# A Distributed Framework for Minimizing the Asymmetrical Power Request in Multi-Agent Microgrids With Unbalanced Integration of DERs

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**ABSTRACT** Microgrids (MGs) are initiated in power systems to speed up the integration of the independently operated distributed energy resources (DERs) into the network. In this regard, in multi-agent microgrids (MAMGs), independent agents aim to operate their resources, while the MG operator (MGO) coordinates independent agents to address the operational issues and ensures reliability of the system. In an MAMG, the high integration of single-phase DERs as well as their independent operational scheduling could result in the asymmetrical power flow in the upper-level system. Respectively, addressing the asymmetrical power request of the MAMGs by exploiting the scheduling of DERs seems to be essential due to the limited flexibility capacity in the upper-level power network, which would finally improve the operating condition of the power system. Consequently, this paper aims to develop a transactive-based scheme to minimize the conceived asymmetrical operation of MAMGs. Accordingly, MGO employs transactive energy signals to minimize the asymmetrical power request of the MAMG by exploiting the scheduling of DERs, while ensuring the privacy of independent agents. Eventually, the proposed framework is applied on an MAMG test system to study its efficacy in alleviating the asymmetrical power request from the upper-level system.

**INDEX TERMS** Multi-agent microgrid, conditional value at risk, CVaR, asymmetrical power flow, unbalanced microgrid, distributed energy resources, renewable energy, flexibility, incentive-based control, transactive control signal.

## NOMENCLATURE

### A. SETS

$i, \Omega_{Agent}$	Index and set of agents.
$t, n$	Scheduling interval and iteration $n$ .
$t'$	Index of time.
$st$	Scenarios.
$ph$	Index of phases.

$I^{L,Agent_i}, I^{BSS,Agent_i}$	Sets of resources of agent $i$ .
$I^{DG,Agent_i}, I^{EV,Agent_i}$	
$Pos/Neg$	Index for increase/decrease in scheduling of resources.
$Dis/Ch$	Index for discharge/charge of BSS/EV.

### B. PARAMETERS

$\rho$	Penalty factor for updating bonus.
$\lambda_{t'}$	Energy price at $t'$ .
$C_k^{LS,Agent_i}$	Load shedding cost for demand $k$ of agent $i$ .

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$\tau_{st,ph}^{Agent_i}$	Probability of $st$ scenario in scheduling of agent $i$ .	$P_{t,ph}^{Agent_i,n}, P_{i,t,ph}^{Agent_i,Prem}$	Accumulated power request of agent $i$ at $t$ in phase $ph$ at iteration $n$ as well as its preliminary scheduling.
$\alpha^{Agent_i}$	Confidence level for considering CVaR method in the scheduling of agent $i$ .		
$\beta^{Agent_i}$	Risk parameter for considering CVaR method in the scheduling of agent $i$ .		
$\Delta P_{t,ph}^{Agent_i,n}$	Change in the preliminary scheduling of resources connected to $ph$ in agent $i$ at $t$ in iteration $n$ of running the framework.		
$\Delta P_{k,t',st,ph}^{Min,Pos/Neg,L,Agent_i}$ , $\Delta P_{k,t',st,ph}^{Max,Pos/Neg,L,Agent_i}$	The minimum/maximum feasible power consumption increase/decrease by load demand $k$ in agent $i$ at $t'$ in scenario $st$ .		
$\Delta P_{k,t',st,ph}^{Max,Pos,Ch/Dis,BSS,Agent_i}$ , $\Delta P_{k,t',st,ph}^{Max,Neg,Ch/Dis,BSS,Agent_i}$	The maximum feasible increase/decrease in power charging/discharging of battery unit $k$ in agent $i$ at $t'$ in scenario $st$ .		
$\Delta P_{i,t',st,ph}^{Max,Pos/Neg,DG,Agent_i}$	The maximum feasible increase/decrease in generation by distributed generation unit $k$ agent $i$ at $t'$ in scenario $st$ .		
$\Delta P_{k,t',st,ph}^{Min,Pos,Ch/Dis,EV,Agent_i}$ , $\Delta P_{k,t',st,ph}^{Min,Neg,Ch/Dis,EV,Agent_i}$ , $\Delta P_{k,t',st,ph}^{Max,Pos,Ch/Dis,EV,Agent_i}$ , $\Delta P_{k,t',st,ph}^{Max,Neg,Ch/Dis,EV,Agent_i}$	The minimum/maximum feasible increase/decrease in charging/discharging of EV unit $k$ in agent $i$ at $t'$ in scenario $st$ .		
$DSOC_{k,t',st,ph}^{Min,BSS/EV,Agent_i}$ , $DSOC_{k,t',st,ph}^{Max,BSS/EV,Agent_i}$	The minimum/maximum feasible modification in state of charge of BSS/EV unit $k$ in agent $i$ at $t'$ in scenario $st$ .		
$E_{k,ph}^{BSS/EV,Agent_i}$	The maximum energy level of BSS/EV unit $k$ connected to phase $ph$ in agent $i$ .		
$SOC_{k,t',ph}^{Requested,Agent_i}$ , $SOC_{k,t',ph}^{Arrival,Agent_i}$	State of charge of EV unit $k$ in agent $i$ , when arriving/leaving the home/station at $t'$ .		
$\eta_{k,ph}^{Ch,BSS/EV,Agent_i}$ , $\eta_{k,ph}^{Dis,BSS/EV,Agent_i}$	The power charging/discharging efficiency of BSS/EV unit $k$ in agent $i$ .		
$C_k^{DG,Agent_i}$	Operational cost of distributed generation unit $k$ in agent $i$ .		
$EDemand_{k,st,ph}^{New,L,Agent_i}$ , $EDemand_{k,st,ph}^{Prem,L,Agent_i}$	New and preliminary expected load demand $k$ in agent $i$ .		
		<b>C. VARIABLES</b>	
		$TE_{t,ph}^n$	Announced transactive control signal in iteration $n$ at $t$ .
		$\psi_{st,ph}^{Agent_i}$	Auxiliary variable of CVaR method in optimization of agent $i$ .
		$\xi_{ph}^{Agent_i}$ , $\xi_{ph}$	Auxiliary variable of CVaR method in optimization of agent $i$ .
		$OF^{Agent_i}$	The objective function of re-scheduling optimization of agent $i$ .
		$\Delta P_{k,t',st,ph}^{Neg,L/DG,Agent_i}$ , $\Delta P_{k,t',st,ph}^{Pos,L/DG,Agent_i}$	The decrease/increase in power request/ generation by load/DG unit $k$ in agent $i$ at $t'$ in scenario $st$ .
		$LS_{k,t',st,ph}^{Agent_i}$	Load shedding of unit $k$ in agent $i$ at $t'$ in scenario $st$ .
		$P_{k,t',st,ph}^{New,L,Agent_i}$ , $P_{k,t',st,ph}^{Prem,L,Agent_i}$	The new/preliminary scheduled power consumption by load demand unit $k$ in agent $i$ at $t'$ in scenario $st$ .
		$\Delta P_{k,t',st,ph}^{Neg,Ch,BSS/EV,Agent_i}$ , $\Delta P_{k,t',st,ph}^{Pos,Ch,BSS/EV,Agent_i}$	The decrease/increase in charging of BSS/EV unit $k$ in agent $i$ at $t'$ in scenario $st$ .
		$\Delta P_{k,t',st,ph}^{Neg,Dis,BSS/EV,Agent_i}$ , $\Delta P_{k,t',st,ph}^{Pos,Dis,BSS/EV,Agent_i}$	The decrease/increase in discharging of BSS/EV unit $k$ in agent $i$ at $t'$ in scenario $st$ .
		$DSOC_{k,t',st,ph}^{BSS/EV,Agent_i}$	The change in state of charge of BSS unit $k$ at $t'$ in scenario $st$ .
		$\Delta P_{i,t,ph}^{Agent_i,n}$	Change in the power request in phase $ph$ at iteration $n$ as well as the preliminary scheduling of agent $i$ at $t$ .
		<b>I. INTRODUCTION</b>	
			Restructuring in energy systems has resulted in development of distributed systems, where operator entities in different levels strive to coordinate the operation of agents in their respective systems [1]. Respectively, microgrids (MGs) with multi-agent structures are developed along with the restructuring and privatization of power systems. In multi-agent MGs (MAMGs), an agent could include a building representing a load, generation resource, battery storage system (BSS), or any combination of these facilities. This structure has facilitated the integration of independently operated distributed energy resources (DERs) into power systems while addressing their privacy concerns. In this context, each agent

autonomously optimizes its resource schedule, while the MG operator (MGO) coordinates the operation of participating agents with the aim of addressing the designated operational constraints.

The unbalanced integration of DERs such as renewable energy sources (RESs), BSSs, and demands in local MGs as well as their independent operation could result in the asymmetrical power flow in the power grid. In other words, due to the unbalanced integration of single-phase DERs, the amount of power requested from the upper-level network would not be similar in all the phases of a multi-agent MG, which would lead to unbalanced power flow in this network. This operational condition could finally cause reliability concerns in the operation of the power grids. In this paper, this operational condition of the MAMG that results in the asymmetrical power transaction with the upper-level network is called the unbalanced operating condition of the MG. In this respect, as a result of the undergoing expansion of decentralized structures in power networks, the resulting asymmetrical power exchange with the power grid should be addressed by MGOs, which will improve reliability of the power system. Based on the defined unbalanced operating condition, new schemes should be developed to enable MGOs to ensure that the power transaction with the upper-network is symmetrical during operation of the MAMG; i.e. the amount of the power exchange between the MAMG and the upper-network becomes equal in all the phases.

Previous research works have addressed energy management of MGs from different perspectives. For example, authors in [2] have developed a distributed control method to securely operate an integrated energy system. Authors in [3] have proposed an optimization model for a MG energy management while minimizing operational cost of the distributed energy resources as well as environmental emission. Reference [4] has studied MAMG energy management. This model considers a photovoltaic unit, a BSS, electrical demand, while developing MG energy management model. In [5], a decentralized optimization model for energy management of a MAMG is developed, where agents optimize their outputs independently. In this methodology, agents are able to interact with each other in a distributed way and attain the effective tactic in a competitive structure. Reference [6] studies different strategies for MG energy management using hierarchical genetic algorithm. In [7], authors have investigated the distributed control methodology for multiple energy bodies while optimizing profits as well as the energy delivery costs in the system. Moreover, learning models have also applied for solving multi-dimensional nonlinear problems in optimizing MGs. Respectively, [8] optimizes MGs energy management utilizing Quantum Teaching Learning-based optimization (QTLBO) algorithm. [9] proposed an energy management model for a MG considering a forecasting structure based on a deep learning model. Nevertheless, while these research works have primarily focused on energy management of MGs, they have overlooked the unbalanced

operating condition in an MAMG due to the unbalanced integration of DERs. Accordingly, these works have not focused on developing and analyzing an approach to ensure the power transaction with the upper-level network is symmetrical during real-time operation of the MAMG.

Operational management schemes in MGs could generally be categorized into centralized and decentralized approaches. In this context, the process of transferring and assessment of local operational data in a central manner could cause privacy concerns in modern distributed systems. Moreover, the transfer and analysis of a huge amount of data require significant communication infrastructures and high computational power, which would finally impede its scalability in decentralized systems. As a result, decentralized approaches have recently received great attention in research works that aim to provide efficient operational strategies in energy systems. Respectively, MGO should employ decentralized methods to address the unbalanced operating condition in a MAMG while addressing agents' privacy concerns.

Recently, the transactive energy (TE) technique has been employed in several research works to develop decentralized management schemes in distributed systems [10]. This approach is based on a value-driven procedure that determines the transactive energy signals (TESs) to coordinate the operation of the system's entities [11]. In other words, the TES is developed to relate the operational objectives to a monetary value in order to incentivize the cooperation of independent agents in the reliable and flexible operation of decentralized systems. As a result, the system operator would be able to exploit the operational scheduling of independent agents without direct access to their resources, which seems to provide secure coordination frameworks for operating the multi-agent structures.

Reference [12] has developed a TE-based energy trading scheme in distribution systems while modeling the technical/economic issues in system management. Furthermore, the authors in [13] have developed a decentralized transactive management algorithm to relieve the pick demand in a multi-agent system. Moreover, a bilateral structure based on the transactive technique is employed in [14] to facilitate the power transactions among agents, which would ensure the balance of supply-demand in energy systems. In [15], the real-time optimization of electric vehicles (EVs) utilizing the TE technique is analyzed for managing the RESs uncertainties as well as maximizing their profits. This paper tried to activate EVs' flexibility by enabling changing their power requests while receiving the optimal TESs. Furthermore, with the aim of maximizing residential buildings profits, a TE-based methodology is developed in [16] to address the privacy of consumers. In addition, bonus-based TE schemes are proposed in [17] and [18] to facilitate local demands participation in providing operational services for system utilities. In this regard, the developed models rely on exchanging the information of local demands to the system operator as well as determining incentive signals associated

with agents contributions in a central manner. Considering above discussions and restructuring in energy systems, decentralized TE-based management of multi-agent structures is an acceptable point of view to address the operational objectives while ensuring privacy concerns.

The unbalanced integration of single-phase DERs in local systems as well as their independent operation would result in the current asymmetry at the common coupling point with the upper-network, which should be addressed by local operators to ensure the reliable operation of power grids. In this regard, authors in [19] have proposed a management scheme to optimize the operation of electric vehicles in the unbalanced distribution grids to ensure the acceptable voltage unbalance condition. Furthermore, [20] presents a scheme to optimize the dispatch of BSSs to address the current and voltage constraints in unbalanced distribution networks. In this regard, it is noteworthy that the resulting unbalanced operating condition in the local systems could also impede the high integration of local DERs such as photovoltaic (PV) units.

A robust optimization model is developed in [21] with the aim of minimizing the unbalanced operating condition while allocating the BSSs in distribution networks. In addition, authors in [22] have proposed a two-stage methodology to optimize installation of single-phase DERs in distribution networks with the aim of mitigating the impact of DERs on the unbalanced operating condition. Moreover, [23] has developed a framework to determine optimal siting/sizing of distributed generations (DGs) in an unbalanced distribution network utilizing the adjustable robust optimization technique. Reference [24] has developed a multi-objective optimization model for scheduling the MGs while striving to minimize the unbalanced operating condition in the system. This strategy shows advantages of considering the unbalanced condition along with operational objectives such as cost minimization and energy savings while scheduling MGs. Authors in [25] have applied different heuristic algorithms to phased multi-objective optimization of active distribution systems. One of the methods to address the unbalance operational condition is to optimize the integration of DERs in energy systems. Respectively, in [26], an approach is developed by utilizing the memory-based artificial gorilla troops optimizer to optimize the installation of biomass DERs in an unbalanced distribution network. Genetic algorithm is taken into account in [27] to optimize the unbalanced distribution systems considering different objectives. Respectively, a non-dominated pareto front is generated with the aim of minimizing the current unbalance and energy loss while considering operational constraints of the system. In addition, [28] has investigated the role of BSSs in the unbalanced-uncertain condition of power systems. The developed management model optimizes the system energy cost, while addressing the load uncertainty and the unbalanced loading in the network. Moreover, authors in [29] have developed an operational model based on the PV re-phasing technique for mitigating

the unbalanced condition of low-voltage distribution networks, which would finally accelerate PVs integration in the system. The literature review shows the importance of addressing the unbalanced operational condition of energy systems during operation and planning stages. Nevertheless, the previous research works have mainly focused on central control of the system to address the asymmetrical operating condition, while the development of multi-agent structures may impede their implementation for managing the asymmetrical power request in modern energy systems.

Based on the above discussions which have been conducted on the management of MGs as well as the unbalanced operating condition in local energy systems, to the best of authors' knowledge, efficient real-time coordination of independent agents in a MAMG to alleviate the asymmetrical power exchange with the upper-network has not yet studied in previous research works. As mentioned earlier, the high integration of single-phase DERs which unevenly generate/consume power in MGs could cause undesired current asymmetry in the upper-network [30]. In other words, the asymmetrical power exchange at the point of common coupling (PCC) of a MAMG and the upper-network could result in an asymmetrical current flow as well as power curtailment in the power grid, which should be addressed utilizing local resources.

This paper aims to exploit the operational scheduling of local DERs to minimize the asymmetrical power exchange at the PCC of a MAMG and the upper-network. In the developed scheme, MGO as a non-profit entity employs TESs to incentivize independent agents' contribution in alleviating the unbalanced operating condition of the MAMG. As a result, the information exchange between the MGO and agents will be limited to accumulated power injections and TESs, which copes with the decentralized nature of the MAMG.

In our proposed framework, independent agents strive to maximize their profits considering the TESs announced by the MGO, while providing operational service to address the unbalanced operating condition. In this regard, MGO would update the TESs interactively to exploit the scheduling of local DERs which can alleviate the asymmetrical power request from the upper-network. In the proposed scheme, model predictive control (MPC) is employed in the scheduling optimization of agents to model the operational condition of future time steps, while managing the operation of DERs at the current time step. Moreover, scenario-based programming and conditional value at risk (CVaR) are deployed in the operational optimization of agents to address the associated risks embedded in decision parameter uncertainties. In addition, the sensitivity analysis is employed to analyze the agents' risk pertaining to final scheduling and optimal TESs. Finally, an optimization model is deployed by the MGO to optimize the decentralized TE scheme and ensure a symmetrical power exchange at the PCC of the MAMG and the upper-network.

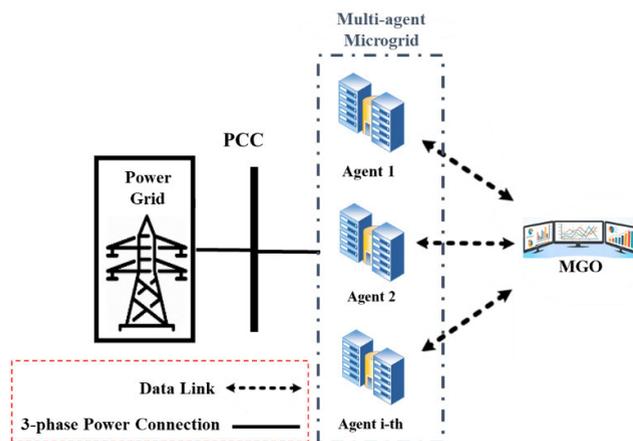
The rest of the paper is organized as follows. Section I covers the MAMG structure and the proposed distributed control

strategy using TESs. Section II delves into the mathematical formulation for updating TESs and the real-time optimization scheduling of local agents. Section III presents the outcomes of applying the developed scheme on a MAMG to mitigate asymmetrical power requests during real-time operations. Finally, Section IV provides the concluding remarks on the proposed approach detailed in the paper.

## II. METHODOLOGY

### A. MAMG MODELING

The integration of private resources into power systems has led to the emergence of MAMGs, where each agent manages its own resources to maximize profit. Within this framework, the MGO is responsible for the coordinated scheduling of agents, ensuring the system operates reliably and flexibly. The decentralized TE-based scheme for agent coordination within the MAMG is illustrated in Fig. 1. Here, the data exchange between agents and the MGO is limited to cumulative power injections and TESs, addressing the privacy concerns of individual agents. This model is versatile, as an agent can represent a local load, distributed generation (DG), RES, BSS, EV, or any combination of these facilities.

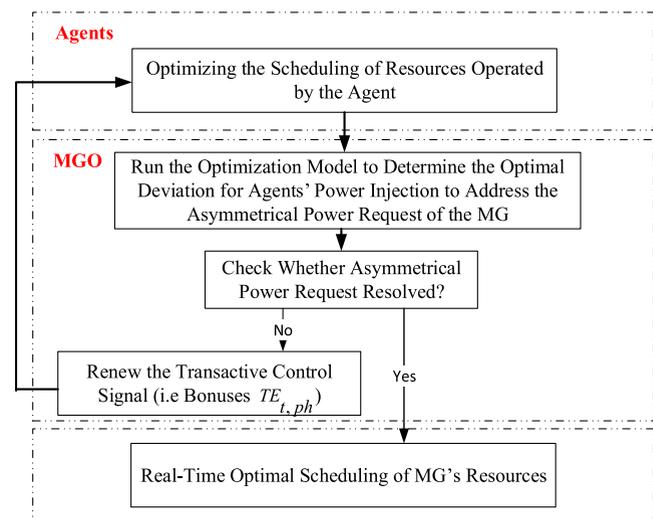


**FIGURE 1.** A simplified model of the management model for mitigating the asymmetrical power exchange between the MAMG and the power grid.

### B. DISTRIBUTED TE-BASED SCHEME

The model introduced in this paper focuses on optimizing the scheduling of independent agents by utilizing incentive signals to address asymmetrical power exchange at the PCC of the MAMG and the upper network. In this approach, TESs are utilized as bonuses to encourage agents to adjust their resource schedules. This allows the MGO to leverage local flexible resources to effectively reduce asymmetrical power demands from system agents. Implementing this scheme ensures voltage and current symmetry in the upper network, facilitating the growth of decentralized structures and the integration of DERs in MAMGs without introducing asymmetrical power flow issues and associated operational challenges.

According to the proposed algorithm, independent agents schedule their local resources based on the received TESs and their operational constraints. The algorithm employs stochastic programming and the CVaR index to address uncertainties and risks in resource scheduling. Additionally, the MPC technique is used to consider future operational conditions while optimizing current resource scheduling. In this scheme, the MGO determines the TES for each phase of the system to adjust power injection by incentivizing resource rescheduling for that phase. The iterative framework for mitigating asymmetrical power exchange at the PCC of the MAMG and the upper network using the TE concept is shown in Fig. 2.



**FIGURE 2.** Proposed scheme for alleviating the asymmetrical power condition in a MAMG.

## III. MATHEMATICAL FORMULATIONS

### A. MGO OPTIMIZATION AND TES DEFINITION

The unbalanced integration of single-phase DERs in the MAMGs could result in the asymmetrical power exchange at the PCC of the MAMG and the upper-level power grid, which would finally cause asymmetry current condition in the upper-network. On the other hand, the independent operation of agents in MAMGs would impede the direct access of the MGO on the scheduling of agents. That is why, in this paper, MGO employs bonuses as TESs to exploit the scheduling of resources in each phase of the system to ensure the symmetrical power exchange between the MAMG and the upper-network. Accordingly, in each iteration of running the proposed scheme, agents in each phase of the grid receive the incentive offers (i.e.  $TES_{t,ph}$ ) to re-schedule their resources.

Based on the developed algorithm, the proposed decentralized TE-based model aims to exploit the preliminary scheduling of agents. In each iteration, MGO firstly determines the mean value of the power requests in different phases of the MAMG. As a result, the mean value of the power request at each phase of the MAMG in iteration  $n$  at  $t$

(i.e.  $P_t^{Mean,MG,n}$ ) could be calculated as follows:

$$P_t^{Mean,MG,n} = \left(\frac{1}{3}\right) \cdot \sum_{ph} \sum_{i \in \Omega_{Agent}} P_{t,ph}^{Agent_i,n} \quad (1a)$$

$$P_{t,ph}^{Agent_i,n} = P_{t,ph}^{Agent_i,Prem} + \Delta P_{t,ph}^{Agent_i,n} \quad (1b)$$

In this regard, in case the asymmetrical power exchange at the PCC of the MAMG and the upper-network is not resolved, the announced TES to agents for optimizing their resources in each phase could be updated as below:

$$TES_{t,ph}^{n+1} = TES_{t,ph}^n + \rho \cdot \left( P_t^{Mean,MG,n} - \sum_{i \in \Omega_{Agent}} P_{t,ph}^{Agent_i,n} \right) \quad (1c)$$

Based on the presented formulation, in case the power request of agents in one phase is more than the mean value, the TES is decreased in comparison with the previous iteration to reduce the power request of the agents connected to the respected phase. Similarly, the TES in iteration  $n$  is increased in case that the power request of agents in one phase is lower than the mean value (i.e.  $P_t^{Mean,MG,n}$ ) to incentivize the increase in their power requests in comparison with the previous iteration. Consequently, the proposed procedure for updating the TESs associated with agents in each phase of the system would enable the MGO to incentivize the contribution of agents in the alleviation of the asymmetrical power request from the upper-network.

Based on the mentioned strategy, in each iteration of conducting the proposed procedure, the power request of the agents as well as  $P_t^{Mean,MG,n}$  are changing, which could challenge the convergence of the proposed method. In other words, by updating the TESs, the increase/decrease in power injections/requests of the resources could again result in the asymmetrical power request from the upper-network. The proposed discontinuous updating procedure of TESs could cause fluctuations in the response of the proposed scheme. That is why an optimization model presented in (2) is developed to be employed by the MGO to determine the permissible changes in the power injection/request of the system agents. Note that the proposed formulation is based on the fact that MGO could request from the agents to change their preliminary power scheduling in each phase in the range of  $\begin{cases} [0, \Delta P_{t,ph}^{Agent_i,n}], \Delta P_{t,ph}^{Agent_i,n} \geq 0 \\ [\Delta P_{t,ph}^{Agent_i,n}, 0], \Delta P_{t,ph}^{Agent_i,n} \leq 0 \end{cases}$  by considering the announced  $TE_{t,ph}^n$  at iteration  $n$ . In the proposed formulation, MGO aims to determine the optimum changes in the preliminary scheduling of agents to alleviate the asymmetrical power request from the upper-network.

$$Min \sum_{ph} \sum_{i \in \Omega_{Agent}} TE_{t,ph}^n \cdot \Delta P_{t,ph}^{Agent_i,Allowable} \quad (2a)$$

$$\Delta P_{t,ph}^{Agent_i,Allowable} = \begin{cases} [0, \Delta P_{t,ph}^{Agent_i,n}], \Delta P_{t,ph}^{Agent_i,n} \geq 0 \\ [\Delta P_{t,ph}^{Agent_i,n}, 0], \Delta P_{t,ph}^{Agent_i,n} \leq 0 \end{cases} \quad (2b)$$

$$P_{t,ph}^{MG,Final} = \sum_{i \in \Omega_{Agent}} \left( P_{t,ph}^{Agent_i,Prem} + \Delta P_{t,ph}^{Agent_i,Allowable} \right) \quad (2c)$$

In the developed formulation, in (2a), MGO strives to minimize the cost associated with the alleviation of the unbalanced operating condition considering the TESs at the respective iteration as well as the permissible changes in the preliminary scheduling of agents. Equation (2b) imposes the boundaries over the changes in the preliminary scheduling of agents, while, (2c) is taken into account to ensure the power balance at the PCC of the MAMG and the upper-network at the respective time interval. It is noteworthy that the proposed model is general and other operating conditions such as the permissible deviation from the mean power value in each phase of the system could be replaced by constraint (2c). The developed formulation in (2) is linear; therefore, the proposed algorithm is considered as converged in the iteration  $n$ , in case the developed optimization model generates the optimal solution. Nevertheless, the non-optimal solution of the optimization model (2) shows that the asymmetrical power exchange with the upper-network has not yet been alleviated, and the algorithm should be continued by updating the TESs as defined in (1c).

In this sub-section, the optimization model conducted by the MGO as well as the updating formulation of the TESs are discussed. In the following sub-sections, the optimization model employed by agents for the scheduling of their respective DERs considering the received TESs from the MGO are explained. In this context, the proposed formulation optimizes the changes in the preliminary scheduling of agents. It is noteworthy that the agents would conduct their own optimization models to optimize the re-scheduling of their resources in each phase, while the MGO updates TESs to incentivize their contribution in the alleviation of the asymmetrical power request by MAMG from the upper-network.

## B. OPTIMIZATION MODELLING OF AGENTS

Agents that schedule DERs could contribute to alleviating of the asymmetrical power request in the MAMG by changing their preliminary scheduling. In other words, the MGO offers TESs to agents in order to incentivize them to change their preliminary scheduling to address the asymmetrical power request from the upper-network. In this regard, Agent  $i$  re-schedules its resources as shown in (3) considering the received TESs from the MGO as well as the operational constraints of the resources. Accordingly, stochastic programming and the CVaR index are employed to model the uncertainty of decision parameters. In addition, the MPC technique is taken into account to consider the operational

condition at future time steps while optimizing the resources at the current time interval (i.e.  $t$ ). It is noteworthy that an agent could control a load, distributed generation (DG), BSS, EV, RES or any combination of these facilities (see (3a)–(3aj), as shown at the pages 8–10).

According to the proposed formulation, the objective function (3a) focuses on maximizing the profits of the  $i_{th}$  agent. The terms within the objective function represent the system's profit at the current time interval ( $t$ ) as well as for the upcoming  $T$  intervals, detailed in (3b)–(3f). This optimization model is designed to be versatile, allowing the agent to manage various flexible resources, such as load demands, DGs, BSSs, EVs, and RESs. Note that  $T^{k,V2G}$  shows the time periods that the EV unit  $k$  is connected to the electrical grid and the respected unit could be charged/discharged. Furthermore, the formulation of the CVaR index is modeled in (3g)–(3i) in order to address the risk associated with uncertain parameters. Accordingly,  $\alpha^{Agent_i}$  represents the confidence level which shows the right tail probability of the density function [31]. Furthermore,  $\beta^{Agent_i}$  is a risk parameter that models the agent's viewpoint towards the uncertainty risk. Note that  $\alpha^{Agent_i}$  and  $\beta^{Agent_i}$  are bounded between 0 and 1; therefore, the risk significance would be increased when  $\beta^{Agent_i}$  is closer to 1 [31].

Notably, equations (3h) and (3i) are used to construct a linear formulation for the CVaR index. The constraint on changes in power consumption by load demands is set by equation (3j), while equation (3k) specifies the energy required for the load during the given time period. Additionally, equations (3l) and (3m) impose constraints on load shedding for each time interval. Limits on the variations in charging/discharging of BSS units are defined by equation (3n). The change in the state of charge of BSS units and its corresponding limits are represented by equations (3o) and (3p), respectively. Furthermore, equations (3q) through (3s) are applied to prevent simultaneous charging and discharging of BSS units within each time interval. In this regard,  $P_{k,t',ph}^{Prem,Dis,BSS}$  /  $P_{k,t',ph}^{Prem,Ch,BSS}$  are preliminary scheduling of the BSS unit  $k$ ; while,  $\alpha_{k,t',st,ph}^{Ch,BSS}$  and  $\alpha_{k,t',st,ph}^{Dis,BSS}$  are binary variables that determine the charging/ discharging mode of the BSS unit. Constraint (3t) is used to limit the variations in the initial scheduling of DG units. Equation (3u) restricts the changes in charging/discharging of EVs. Changes in the state of charge for EVs, along with their respective bounds, are represented by equations (3v) and (3w). The charging state of the EV battery at arrival/departure times is modeled by equations (3x) and (3y). To prevent simultaneous charging/discharging of EVs at any given time, constraints (3z)–(3ab) are applied. Constraint (3ac) limits changes in the preliminary scheduling of RES units. The cumulative changes in preliminary scheduling for load demand, RESs, BSSs, DGs, and EVs are determined by constraints (3ad)–(3ah). Additionally, equation (3ai) reflects the total change in the power request by agent  $i$  at time  $t$  to be communicated to the MGO. Finally, equation (3aj)

ensures that the agent receives a bonus only if it contributes to alleviating power unbalances in the system.

A simplified model of the algorithm developed in this paper to resolve the asymmetrical power request of the MAMG from the upper-network utilizing local flexible resources is shown as below:

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#### Algorithm Alleviating the Asymmetrical Power Request by Multi-Agent MG

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```

1. Start
2. Input data
3. While true
    Every Agent: solve (3)
    MGO: solve (2)
    if optimization (2) results in non-optimal condition
        MGO: Calculate the updated  $TES_{t,ph}^{n+1}$  (1c)
    else
        MGO: Announce  $\Delta P_{t,ph}^{Agent_i, Allowable}$ 
        Break
    End
4. End

```

---

#### IV. CASE STUDY

The developed framework is applied on an MAMG system to scrutinize its performance and its usefulness in rectifying the asymmetrical power request by the MAMG from the upper-network. As reviewed before, this condition arises due to an unbalanced integration of DERs and their autonomous functioning within the MAMG. For this study, the presumptions include the presence of RESs (i.e. PV and wind power units), ESSs, EVs, flexible demands, and DGs within the system, which are scheduled by autonomous agents [18], [32]. In the simulation, it is considered that each agent operates a solo DERs type to facilitate comparing their impact in mitigating the asymmetrical power request by the MAMG. The MGO, according to the designed approach, coordinates the agent operations to rectify the asymmetrical power request. In response, these agents independently re-plan their resources considering the TESs received from the MGO. They also utilize stochastic programming to account for the unpredictability in decision parameters (like operational limitations of resources and power prices) along with the CVaR index for managing their respective risks.

The preliminary study delved into the operational optimization of the system over a 24-hour operational period to alleviate asymmetrical power request by MAMG. Assuming a risk factor of 0.2 in the resource re-scheduling optimizations conducted by the agents, Figs. 3 & 4 show the power exchanges between the MAMG and the upper-level network before and after the suggested framework's implementation. The results suggest that leveraging this framework can help addressing power unbalances in a distributed manner while maintaining the privacy of autonomous resources. In essence, this strategy could be used by utilities to reduce the asymmetrical power request by MAGMs. In this regard, the voltage and current asymmetry at the power networks due to

$$\text{Max} \sum_{ph} OF_{ph}^{Agent_i} \tag{3a}$$

$$\text{Subject to: } OF_{st,ph}^{Agent_i,3} = OF_{st,ph}^{Agent_i,1} + OF_{st,ph}^{Agent_i,2} \tag{3b}$$

$$OF_{st,ph}^{Agent_i,1} = \left( \begin{array}{l} Bonus_{t',ph}^{Agent_i} + \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{L,Agent_i} + \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{BSS,Agent_i} \\ + \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{DG,Agent_i} + \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{RES,Agent_i} \\ + \sum_{k \in I^{L,Agent_i}} \left( -LS_{k,t',st,ph}^{Agent_i} \cdot C_k^{LS,Agent_i} \right) \\ + \sum_{k \in I^{DG}} \left( \left( \begin{array}{l} \Delta P_{k,t',st,ph}^{Neg,DG,Agent_i} \\ -\Delta P_{k,t',st,ph}^{Pos,DG,Agent_i} \end{array} \right) C_{k,ph}^{DG,Agent_i} \right) \end{array} \right) \Big|_{t'=t} \\ + \left( \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{EV,Agent_i} \right) \Big|_{t'=t} \\ \&t' \in T^{k,V2G} \tag{3c}$$

$$OF_{st,ph}^{Agent_i,2} = \sum_{t' \in [t+1, t+T]} \left( \begin{array}{l} \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{L,Agent_i} + \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{BSS,Agent_i} \\ + \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{DG,Agent_i} + \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{RES,Agent_i} \\ + \sum_{k \in I^{L,Agent_i}} \left( -LS_{k,t',st,ph}^{Agent_i} \cdot C_k^{LS,Agent_i} \right) \\ + \sum_{k \in I^{DG}} \left( \left( \begin{array}{l} \Delta P_{k,t',st,ph}^{Neg,DG,Agent_i} \\ -\Delta P_{k,t',st,ph}^{Pos,DG,Agent_i} \end{array} \right) C_{k,ph}^{DG,Agent_i} \right) \end{array} \right) \\ + \sum_{t' \in [t+1, t+T]} \left( \lambda_{t',st} \cdot \Delta PS_{t',st,ph}^{EV,Agent_i} \right) \\ \&t' \in T^{k,V2G} \tag{3d}$$

$$OF_{ph}^{Agent_i,4} = \sum_{st} \left( \tau_{st,ph}^{Agent_i} \cdot OF_{st,ph}^{Agent_i,3} \right) \tag{3e}$$

$$OF_{ph}^{Agent_i} = (1 - \beta^{Agent_i}) \cdot OF_{ph}^{Agent_i,4} + \beta^{Agent_i} \cdot OF_{ph}^{Agent_i,5} \tag{3f}$$

$$OF_{ph}^{Agent_i,5} = \xi_{ph}^{Agent_i} - \left( 1 / (1 - \alpha^{Agent_i}) \right) \cdot \sum_{st} \left( \tau_{st,ph}^{Agent_i} \cdot \psi_{st,ph}^{Agent_i} \right) \tag{3g}$$

$$\xi_{ph}^{Agent_i} - OF_{st,ph}^{Agent_i,3} \leq \psi_{st,ph}^{Agent_i} \tag{3h}$$

$$\psi_{st,ph}^{Agent_i} \geq 0 \tag{3i}$$

$$\Delta P_{k,t',st,ph}^{Min,Pos/Neg,L,Agent_i} \leq \Delta P_{k,t',st,ph}^{Pos/Neg,L,Agent_i} \\ \leq \Delta P_{k,t',st,ph}^{Max,Pos/Neg,L,Agent_i} \tag{3j}$$

$$\sum_{t' \in [t, t+T]} \left( \begin{array}{l} \Delta P_{k,t',st,ph}^{Pos,L,Agent_i} \\ -\Delta P_{k,t',st,ph}^{Neg,L,Agent_i} \end{array} \right) = EDemand_{k,st,ph}^{New,L,Agent_i} \\ - EDemand_{k,st,ph}^{Prem,L,Agent_i} \tag{3k}$$

$$P_{k,t',st,ph}^{New,L,Agent_i} = P_{k,t',st,ph}^{Prem,L,Agent_i} + \Delta P_{k,t',st,ph}^{Pos,L,Agent_i} - \Delta P_{k,t',st,ph}^{Neg,L,Agent_i} \tag{3l}$$

$$0 \leq LS_{k,t',st,ph}^{Agent_i} \leq P_{k,t',st,ph}^{New,L,Agent_i} \tag{3m}$$

$$0 \leq \Delta P_{k,t',st,ph}^{Pos/Neg,Ch/Dis,BSS,Agent_i} \\ \leq \Delta P_{k,t',st,ph}^{Max,Pos/Neg,Ch/Dis,BSS,Agent_i} \tag{3n}$$

$$DSOC_{k,t'+1,st,ph}^{BSS,Agent_i} = DSOC_{k,t',st,ph}^{BSS,Agent_i} + \left( \frac{1}{E_{k,ph}^{BSS,Agent_i}} \right) \cdot \left( \begin{array}{c} \eta_{k,ph}^{Ch,BSS,Agent_i} \left( \begin{array}{c} \Delta P_{k,t',st,ph}^{Pos,Ch,BSS,Agent_i} \\ -\Delta P_{k,t',st,ph}^{Neg,Ch,BSS,Agent_i} \end{array} \right) \\ - \left( \begin{array}{c} \Delta P_{k,t',st,ph}^{Pos,Dis,BSS,Agent_i} \\ -\Delta P_{k,t',st,ph}^{Neg,Dis,BSS,Agent_i} \end{array} \right) / \eta_{k,ph}^{Dis,BSS,Agent_i} \end{array} \right) \quad (30)$$

$$DSOC_{k,t',st,ph}^{Min,BSS,Agent_i} \leq DSOC_{k,t',st,ph}^{BSS,Agent_i} \leq DSOC_{k,t',st,ph}^{Max,BSS,Agent_i} \quad (3p)$$

$$0 \leq P_{k,t',ph}^{Prem,Ch,BSS,Agent_i} + \Delta P_{k,t',st,ph}^{Pos,Ch,BSS,Agent_i} - \Delta P_{k,t',st,ph}^{Neg,Ch,BSS,Agent_i} \leq P_{k,ph}^{Max,Ch,BSS,Agent_i} \cdot \alpha_{k,t',st,ph}^{Ch,BSS,Agent_i} \quad (3q)$$

$$0 \leq P_{k,t',ph}^{Prem,Dis,BSS,Agent_i} + \Delta P_{k,t',st,ph}^{Pos,Dis,BSS,Agent_i} - \Delta P_{k,t',st,ph}^{Neg,Dis,BSS,Agent_i} \leq P_{k,ph}^{Max,Dis,BSS,Agent_i} \cdot \alpha_{k,t',st,ph}^{Dis,BSS,Agent_i} \quad (3r)$$

$$\alpha_{k,t',st,ph}^{Ch,BSS,Agent_i} + \alpha_{k,t',st,ph}^{Dis,BSS,Agent_i} \leq 1 \quad (3s)$$

$$0 \leq \Delta P_{k,t',st,ph}^{Pos/Neg,DG,Agent_i} \leq \Delta P_{k,t',st,ph}^{Max,Pos/Neg,DG,Agent_i} \quad (3t)$$

$$\Delta P_{k,t',st,ph}^{Min,Pos/Neg,Ch/Dis,EV,Agent_i} \leq \Delta P_{k,t',st,ph}^{Pos/Neg,Ch/Dis,EV,Agent_i} \leq \Delta P_{k,t',st,ph}^{Max,Pos/Neg,Ch/Dis,EV,Agent_i} \quad (3u)$$

$$DSOC_{k,t'+1,st,ph}^{EV,Agent_i} = DSOC_{k,t',st,ph}^{EV,Agent_i} + \frac{1}{E_{k,ph}^{EV,Agent_i}} \times \left( \begin{array}{c} \eta_{k,ph}^{Ch,EV,Agent_i} \left( \begin{array}{c} \Delta P_{k,t',st,ph}^{Pos,Ch,EV,Agent_i} - \Delta P_{k,t',st,ph}^{Neg,Ch,EV,Agent_i} \end{array} \right) \\ - \left( \begin{array}{c} \Delta P_{k,t',st,ph}^{Pos,Dis,EV,Agent_i} - \Delta P_{k,t',st,ph}^{Neg,Dis,EV,Agent_i} \end{array} \right) / \eta_{k,ph}^{Dis,EV,Agent_i} \end{array} \right) \quad (3v)$$

$$DSOC_{k,t',st,ph}^{Min,EV,Agent_i} \leq DSOC_{k,t',st,ph}^{EV,Agent_i} \leq DSOC_{k,t',st,ph}^{Max,EV,Agent_i} \quad (3w)$$

$$SOC_{k,t',ph}^{Prem,EV,Agent_i} + DSOC_{k,t',st,ph}^{EV,Agent_i} = SOC_{k,t',ph}^{Requested,Agent_i}, t' = t_k^{out} \quad (3x)$$

$$SOC_{k,t',ph}^{Prem,EV,Agent_i} + DSOC_{k,t',st,ph}^{EV,Agent_i} = SOC_{k,t',ph}^{Arrival,Agent_i}, t' = t_k^{arrive} \quad (3y)$$

$$0 \leq P_{k,t',ph}^{Prem,Ch,EV,Agent_i} + \Delta P_{k,t',st,ph}^{Pos,Ch,EV,Agent_i} - \Delta P_{k,t',st,ph}^{Neg,Ch,EV,Agent_i} \leq P_{k,ph}^{Max,Ch,EV,Agent_i} \cdot \alpha_{k,t',st,ph}^{Ch,EV,Agent_i} \quad (3z)$$

$$0 \leq P_{k,t',ph}^{Prem,Dis,EV,Agent_i} + \Delta P_{k,t',st,ph}^{Pos,Dis,EV,Agent_i} - \Delta P_{k,t',st,ph}^{Neg,Dis,EV,Agent_i} \leq P_{k,ph}^{Max,Dis,EV,Agent_i} \cdot \alpha_{k,t',st,ph}^{Dis,EV,Agent_i} \quad (3aa)$$

$$\alpha_{k,t',st,ph}^{Ch,EV,Agent_i} + \alpha_{k,t',st,ph}^{Dis,EV,Agent_i} \leq 1 \quad (3ab)$$

$$0 \leq \Delta P_{k,t',st,ph}^{Pos/Neg,RES,Agent_i} \leq \Delta P_{k,t',st,ph}^{Max,Pos/Neg,RES,Agent_i} \quad (3ac)$$

$$\Delta PS_{t',st,ph}^L, Agent_i = \sum_{k \in I^L} \left( \Delta P_{k,t',st,ph}^{Neg,L,Agent_i} - \Delta P_{k,t',st,ph}^{Pos,L,Agent_i} \right) \quad (3ad)$$

$$\Delta PS_{t',st,ph}^{RES,Agent_i} = \sum_{k \in I^{RES}} \left( \Delta P_{k,t',st,ph}^{Pos,RES,Agent_i} - \Delta P_{k,t',st,ph}^{Neg,RES,Agent_i} \right) \quad (3ae)$$

$$\Delta PS_{t',st,ph}^{BSS,Agent_i} = \sum_{k \in I^{BSS}} \left( \begin{array}{c} \Delta P_{k,t',st,ph}^{Neg,Ch,BSS,Agent_i} \\ + \Delta P_{k,t',st,ph}^{Pos,Dis,BSS,Agent_i} \\ - \Delta P_{k,t',st,ph}^{Pos,Ch,BSS,Agent_i} \\ - \Delta P_{k,t',st,ph}^{Neg,Dis,BSS,Agent_i} \end{array} \right) \quad (3af)$$

$$\Delta PS_{t',st,ph}^{DG,Agent_i} = \sum_{k \in I^{DG}} \left( \Delta P_{k,t',st,ph}^{Pos,DG,Agent_i} - \Delta P_{k,t',st,ph}^{Neg,DG,Agent_i} \right) \quad (3ag)$$

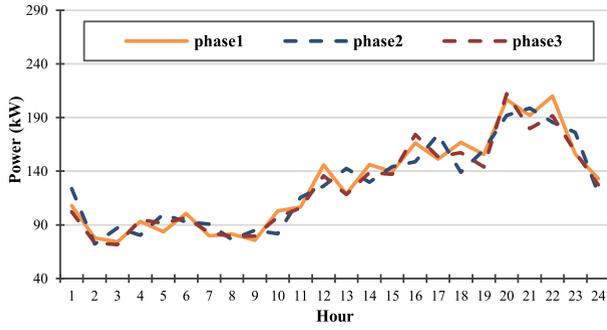


FIGURE 3. Power request by MAMG before implementing the proposed scheme at each real-time interval of operating the system.

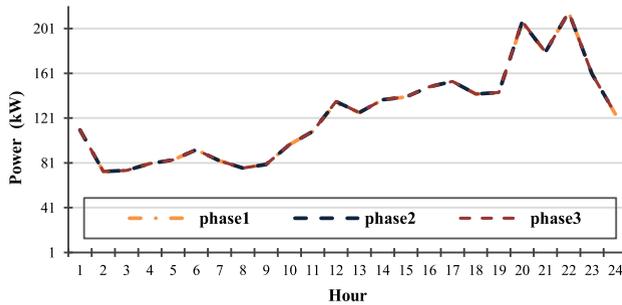


FIGURE 4. Power request by MAMG after implementing the proposed scheme at each real-time interval of operating the system.

the unbalance integration of DERs in local systems would be alleviated, resulting in enhanced system reliability and flexibility. As mentioned, the changes in the preliminary scheduling of resources at each time interval enable the MGO to mitigate the power unbalance condition. Changes in load demands, BSSs, EVs, and DGs' preliminary scheduling while implementing the proposed framework are displayed in Figs. 5 – 12. The power requests of the agents in phases 1 and 3 are seen to decrease at the 24<sup>th</sup> time interval, while phase 2 sees an increase at this same hour. Conversely, at hour 13, demand, BSSs, and DGs in phases 1 and 3 see an increase in power request, while BSSs and DGs in phase 2 experience a reduction. On the hand, at hour 22, the power request

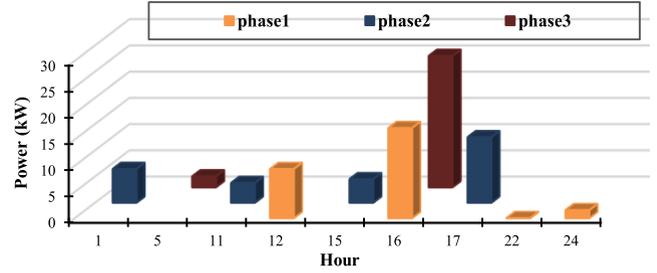


FIGURE 5. Decrease in the power request of loads after implementing the proposed scheme.

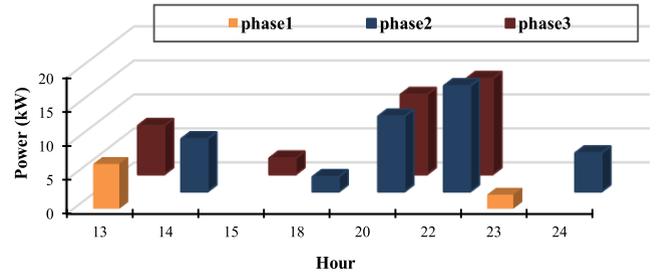


FIGURE 6. Increase in the power request of loads after implementing the proposed scheme.

of loads in phase 1 (shown in Fig. 5) is decreased, while the power request by BSSs/EVs in phase 2 and 3 (shown in Figs. 8 & 10) is increased to alleviate the asymmetrical power request at this time interval. It is clear that even the increase in power request in phase 2 is more than phase 3 by BSSs/EVs as the preliminary power request by phase 2 was lower than phase 3 based on the results shown in Fig. 3.

The results show that the system's asymmetrical power request improves through local flexibility capacity, enhancing the power grid's adaptability. Agents are rewarded only if they contribute to reducing the power unbalance condition in the system, which was modelled by mathematical formulations (3p), (3r), (3m), and (3t). The share of resources contributing to the needed flexibility capacity to address the asymmetrical power request by MAMG at each interval in this case study is represented in Fig. 13.

$$\Delta PS_{t',st,ph}^{EV,Agent_i} = \sum_{k \in I^{EV}} \begin{pmatrix} \Delta P_{k,t',st,ph}^{Neg,Ch,EV,Agent_i} \\ -\Delta P_{k,t',st,ph}^{Pos,Ch,EV,Agent_i} \\ +\Delta P_{k,t',st,ph}^{Pos,Dis,EV,Agent_i} \\ -\Delta P_{k,t',st,ph}^{Neg,Dis,EV,Agent_i} \end{pmatrix} \quad (3ah)$$

$$\Delta P_{t',ph}^{Agent_i} = -\sum_{st} \tau_{st,ph}^{Agent_i} \cdot \begin{pmatrix} \Delta PS_{t',st,ph}^{L,Agent_i} + \Delta PS_{t',st,ph}^{RES,Agent_i} \\ +\Delta PS_{t',st,ph}^{BSS,Agent_i} \\ +\Delta PS_{t',st,ph}^{DG,Agent_i} + \Delta PS_{t',st,ph}^{EV,Agent_i} \end{pmatrix}, t' = t \quad (3ai)$$

$$Bonus_{t',ph}^{Agent_i} = \begin{cases} \Delta P_{t',ph}^{Agent_i} \cdot TE_{t',ph}, \Delta P_{t',ph}^{Agent_i} \cdot TE_{t',ph} \geq 0, t' = t \\ 0, \Delta P_{t',ph}^{Agent_i} \cdot TE_{t',ph} < 0, t' = t \end{cases} \quad (3aj)$$

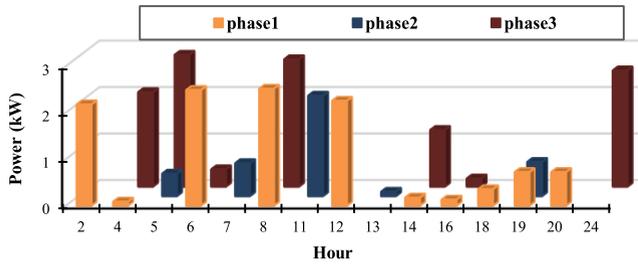


FIGURE 7. Decrease in the power request of BSSs after implementing the proposed scheme.

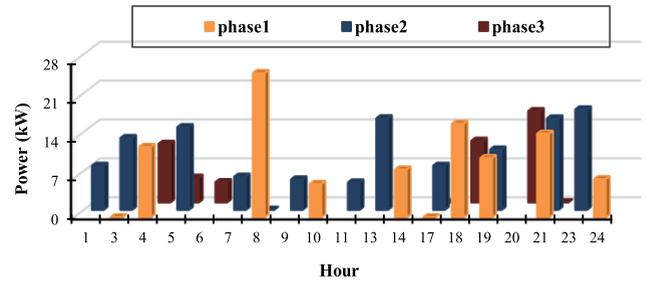


FIGURE 11. Decrease in the power request of DGs after implementing the proposed scheme.

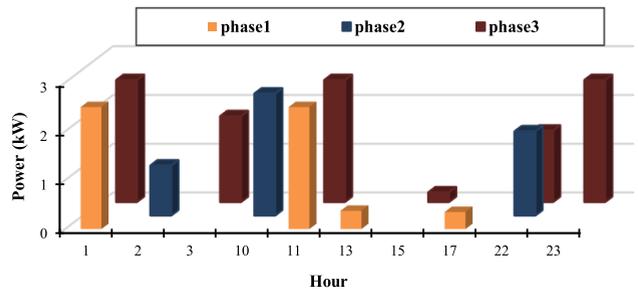


FIGURE 8. Increase in the power request of BSSs after implementing the proposed scheme.

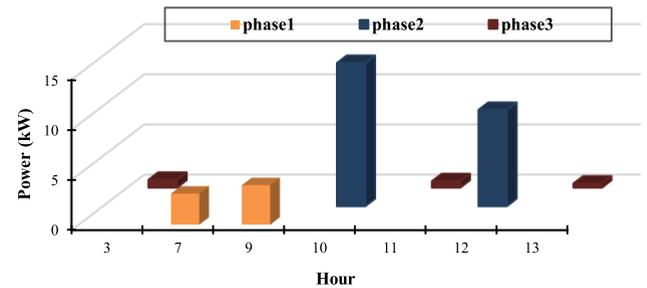


FIGURE 12. Increase in the power request of DGs after implementing the proposed scheme.

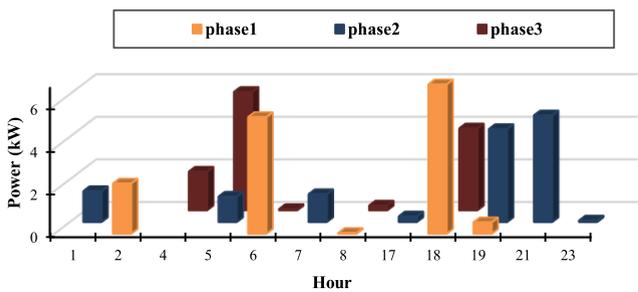


FIGURE 9. Decrease in the power request of EVs after implementing the proposed scheme.

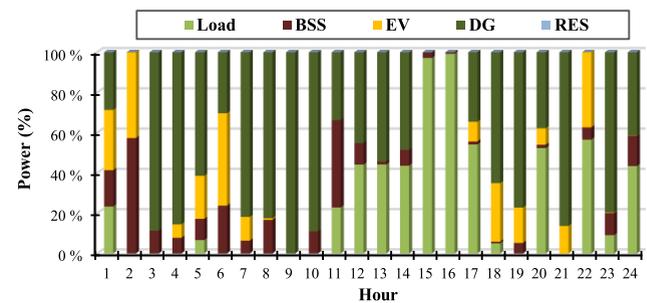


FIGURE 13. Contribution of the resources in the MAMG in mitigating the asymmetrical power request condition at each time interval in case of  $\beta = 0.2$ .

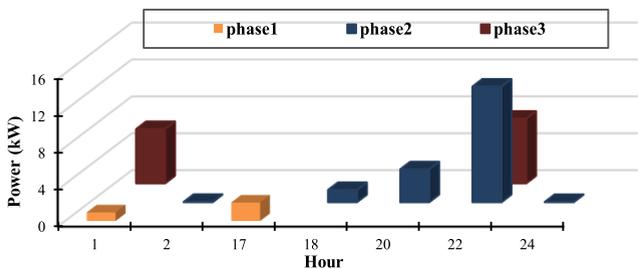


FIGURE 10. Increase in the power request of EVs after implementing the proposed scheme.

In the second case study, the application of the proposed approach in the case of considering different risk factors (i.e.  $\beta$ ) in the optimization modeling of agents is studied. In this respect, the overall amount of bonuses received by local resources during the 24 hours for contributing in the proposed algorithm is shown in Fig. 14. Based on the obtained results, as the agents become more risk-averse, flexible agents

would be less keen to contribute in the asymmetrical power alleviation process due to the future uncertainties and their respective risks. That is why the power generation by RESs is decreased in case the risk factor equals 0.8 and 1. Note that the contribution of RESs is compensated by the received bonuses. In this context, the offered TESs in case of considering the risk factor (i.e.  $\beta$ ) of 0.2 and 1 are represented in Figs. 15 and 16. Note that, as the agents become more risk-averse, the MGO has to offer higher TESs to incentivize their contribution in alleviating the asymmetrical power request by MAMG from the upper-network. Overall, the proposed model facilitates the contribution of local resources in providing the operational service for alleviating the power unbalance condition in the system, while considering the uncertainty of decision parameters such as energy prices in future time intervals. Finally, the developed approach facilitates the high integration of DERs in local energy systems by alleviating

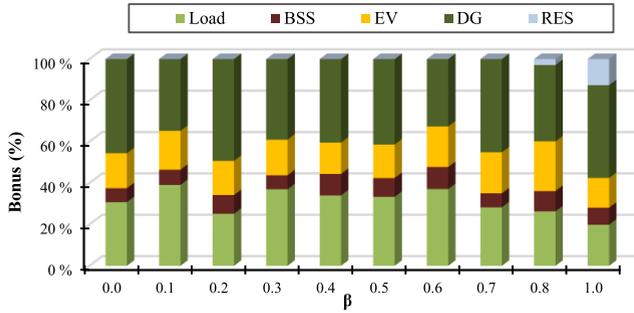


FIGURE 14. Share of each kind of local resource in the total amount of bonuses received in different case studies.

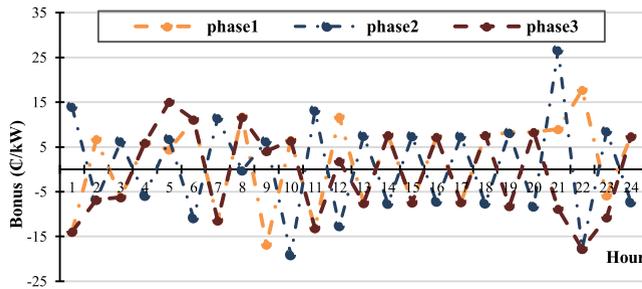


FIGURE 15. Transactive signals announced by the MGO in case of  $\beta = 0.2$ .

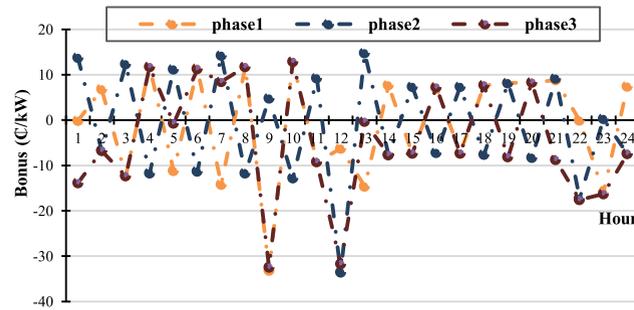


FIGURE 16. Transactive signals announced by the MGO in the case of  $\beta = 1$ .

their associated operational issue (i.e. asymmetrical power request condition) utilizing the local flexible resources.

## V. DISCUSSIONS

In this paper, it is assumed that the MGO as the system operator coordinates the agents re-scheduling to balance the power exchange of the MG with the upper-network. However, the proposed model could be effortlessly expanded for modeling the power unbalance regulations in future power networks. In this context, in a general point of view, the regulation could be modeled as a bounding factor for the power exchange at each phase of the system with the upper network as follows:

$$P_{t,ph}^{n,MG} = \sum_{i \in \Omega_{Agent}} P_{i,t,ph}^n \quad (4a)$$

$$(1 - \kappa) \leq \left| \frac{P_{t,ph}^{n,MG}}{P_t^{Mean,MG,n}} \right| \leq (1 + \kappa) \quad (4b)$$

In this regard, the mathematical formulation of the optimization conducted by the MGO in (2) should be revised to consider this constraint. However, as the (4b) is non-linear, (4b) is firstly replaced by the following formulations to become linear:

$$P_t^{Mean,MG,n} = P_t^{Mean,MG,n,Positive} - P_t^{Mean,MG,n,Negative} \quad (5a)$$

$$0 \leq P_t^{Mean,MG,n,Positive} \leq M \cdot \theta_{i,t}^{MG,n,Positive} \quad (5b)$$

$$0 \leq P_t^{Mean,MG,n,Negative} \leq M \cdot \theta_{i,t}^{MG,n,Negative} \quad (5c)$$

$$\theta_{i,t}^{MG,n,Positive} + \theta_{i,t}^{MG,n,Negative} \leq 1 \quad (5d)$$

$$\begin{aligned} (1 - \kappa) \cdot P_t^{Mean,MG,n,Positive} + (1 + \kappa) P_t^{Mean,MG,n,Negative} \\ \leq P_{t,ph}^{n,MG} \\ \leq (1 + \kappa) \cdot P_t^{Mean,MG,n,Positive} \\ + (1 - \kappa) P_t^{Mean,MG,n,Negative} \end{aligned} \quad (5e)$$

where,  $\theta_{i,t}^{MG,n,Positive}$  and  $\theta_{i,t}^{MG,n,Negative}$  are binary variables. Moreover,  $\kappa$  shows the permissible deviation from the mean value to ensure the power request at each phase is bounded. As a result, the optimization model (2) conducted by the MGO in the proposed framework could be replaced by the following formulation to employ the considered power unbalance constraint (4b).

$$\text{Min} \sum_{ph} \sum_{i \in \Omega_{Agent}} TE_{t,ph}^n \cdot \Delta P_{i,t,ph}^{Allowable} \quad (6a)$$

Subject to (5a) – (5e) and

$$\Delta P_{i,t,ph}^{Allowable} = \begin{cases} \left[ 0, \Delta P_{i,t,ph}^n \right], \Delta P_{i,t,ph}^n \geq 0 \\ \left[ \Delta P_{i,t,ph}^n, 0 \right], \Delta P_{i,t,ph}^n \leq 0 \end{cases} \quad (6b)$$

$$P_{t,ph}^{n,MG} = \sum_{i \in \Omega_{Agent}} \left( P_{i,t,ph}^{Prem} + \Delta P_{i,t,ph}^{Allowable} \right) \quad (6c)$$

$$P_t^{Mean,MG,n} = \left( \frac{1}{3} \right) \cdot \sum_{ph} P_{t,ph}^{n,MG} \quad (6d)$$

This optimization model is linear and convex. In this regard, the proposed formulation enables the MGO to determine the changes in the preliminary scheduling of resources while addressing the asymmetrical power request constraint (4b). Note that the algorithm would be stopped in case the optimization (6) converges to the optimal solution. However, the TES would be updated and the algorithm continues in case the optimization model (6) does not converge to the optimal solution at iteration  $n$  of running the proposed step-wise algorithm in Fig. 2.

## VI. CONCLUSION

This study presents an approach to effectively navigate the scheduling of agents within an MAMG, aiming to manage asymmetrical power request in a distributed fashion. It's essential to denote that asymmetrical power request from the MAMG, as a result of unbalanced integration of DERs,

asymmetry current as well as power curtailment in the upper-network. As a consequence, the suggested approach could enhance the robustness and adaptability of power networks.

In the recommended strategy, the MGO incentivizes the participating agents by offering bonuses in the form of TESs, inspiring their participation in reducing the asymmetrical power request by MAMG. Agents, in response, rearrange their resources independently, acknowledging the bonus signals offered by the MGO and their resources' operational limitations. As a result, the information exchange between the agents and the MGO is restricted to the aggregated power demand and TESs. This approach ensures the privacy and security of independent agents are maintained while they offer operational services to minimize the asymmetrical power request within the system. To accommodate decision parameters' uncertainty and their associated risks, the optimization modeling of agents utilized stochastic programming alongside the CVaR index.

The proposed strategy was applied to an MAMG comprising independent agents managing DGs, EVs, BSSs, RESs, and load demands. Simulations demonstrate the designed model's effectiveness in reducing the asymmetrical power request by the MAMG from the upper-network. Furthermore, the impact of the tendency of agents to take risk or avoid it on the implementation of the proposed scheme was assessed in the case studies.

In the end, the results indicated that the evolved approach would efficiently decrease power unbalances within the MAMG in a cost-effective way. This would, in turn, improves the robustness and adaptability of power networks. In future studies, the developed approach will be adapted based on the available decentralized operational management techniques (e.g. consensus-based alternating direction method of multipliers) to study its potential in activating flexibility in each phase of a MAMG to address the local operational issues in the system.

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