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A new management framework for mitigating intense ramping in distribution systems

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A B S T R A C T

Nowadays, the increasing integration of variable renewable energies (VREs) in power systems have resulted in operational transformations of energy systems. Respectively, the high-amount of integrated VREs could cause severe-ramping in the net-load of energy systems due to abrupt changes in their power production. Accordingly, based on the limited flexibility capacity in transmission systems, severe ramping-up/down (RU/RD) in distribution systems should be addressed by employing local flexible resources (LFRs). Nevertheless, evolution of multi-agent structured distribution systems has limited the direct access of distribution system operators (DSOs) in scheduling of LFRs. Consequently, this paper intends to organize a bonus-based framework for flexibility RU/RD management in multi-agent distribution systems (MADSs). In this approach, each agent independently operates its resources, while DSO strives to efficiently manage the intense RU/RD associated with the MADS's net electricity demand. Respectively, the proposed approach is modeled as a Stackelberg game and the strong duality concept is deployed to construct the one-level optimizing formulation to determine its equilibrium point. Subsequently, the proposed strategy enables the contribution of LFRs in the RU/RD management of energy systems with high-amount of integrated VREs. Finally, the proposed strategy is applied on a 37-bus-test-system to examine its effectiveness in severe RU/RD mitigation in MADSs.

1. Introduction

Increasing integration of variable renewable energies (VREs) as a result of environmental challenges and governmental support in power systems has initiated new challenges in operating the energy systems [1,2]. In this regard, management procedures of energy systems should be updated based on the stochastic and intermittent behavior of VREs. Accordingly, flexibility ramping-up/down (RU/RD) capacity in power systems should be managed in an efficient manner to ensure that the load-supply balance in each area of the system would be addressed in case of abrupt changes in the power production of VREs [46].

Power production by VREs, i.e. wind power and photovoltaic (PV) units, primarily depends on the environmental characteristics which could result in its sudden changes [3]. In this context, according to the ramping challenges in the California network [4], the increasing load demand in evening time periods as well as the decreasing power generation by PV units could engender severe RU/RD in the system's net electricity demand and finally put into risk the process of operating the energy system in a reliable manner [5,6]. Consequently, system operators should ensure the reliable and flexible operation of energy systems by securing flexibility RU/RD capacity to address the increasing gap between supply and demand.

System operators have conventionally been dependent on fast bulk power units connected to transmission grids in order to secure flexibility RU/RD capacity in the system. Nevertheless, the high cost of investment and operation of bulk power units compared with the decreasing investment costs and low operational costs of VREs show the necessity of acquiring ramp-service from local flexible resources (LFRs). On the other hand, the potential congestion occurrences in the system as well as the expansion of distributed systems have resulted in the introduction of the zonal flexibility

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Nomenclature

A. Sets

i	Index used to present the number of the nodes in the distribution grid
i_0	The connecting node of the distribution grid to the transmission grid
t	T Index used to present time interval and the optimization horizon

B. Constants

$\Delta P_{i,t}^{Max,Pos,G}$, $\Delta P_{i,t}^{Max,Neg,G}$	Possible maximum amount of increasing/decreasing the power generation of conventional distributed generations (CDGs) in node i at t
$\Delta P_{i,t}^{Max,Pos,Dis,S}$, $\Delta P_{i,t}^{Max,Neg,Dis,S}$	Possible maximum amount of increasing/decreasing the power-discharging of the storages in node i at t
$\Delta P_{i,t}^{Max,Pos,Ch,S}$, $\Delta P_{i,t}^{Max,Neg,Ch,S}$	Possible maximum amount of increasing/decreasing the power-charging of storages in node i at t
$\eta_i^{Ch,S}$, $\eta_i^{Dis,S}$	Efficiency associated with the power-charging and power-discharging of storages in node i
E_i^S	Energy capacity of storages in node i
$\Delta P_{i,t}^{Max,Pos,D}$ $\Delta P_{i,t}^{Max,Neg,D}$	Possible maximum amount of increasing/decreasing the consumption power of flexible demands in node i at t
$DSOC_{i,t}^{Max,S}$ $DSOC_{i,t}^{Min,S}$	Possible maximum amount of increasing/decreasing the state of the charge of storages in node i at t
$P_{i,t}^{Max,Ch,S}$, $P_{i,t}^{Max,Dis,S}$	Possible maximum amount of power-charging/discharging of ESSs in node i at t
$P_{i,t}^{DA,Ch,S}$, $P_{i,t}^{DA,Dis,S}$	Day-ahead scheduling of the power-charging/discharging of storage units in node i at t
$\Delta P_{i,t}^{Max,Wind}$	Possible maximum amount of the power production by wind power in node i at t
$\Delta P_{i,t}^{Max,PV}$	Possible maximum amount of the power production by photovoltaic power in node i at t
$P_{i,t}^{Scheduled}$	Power exchange between the distribution grid and node i based on the day-ahead planning at t
$Ramp^{up,Max}$, $Ramp^{down,Max}$	Limitations associated with the RU/RD in the system
$C_{i,t}^{LS}$	Cost value associated with shedding the load demand in node i at t
$C_{i,t}^{VRE}$	Cost value associated with the power curtailment of renewable energies in node i at t
$Load_{i,t}^{Scheduled}$	Power consumption by the load in day-ahead scheduling in node i at t
$Q_{i,t}$	The amount of the reactive power exchange in node i at t
$r_{i,j}^{DG}$	The value of the resistance associated with the line connecting node i and j in the distribution grid
$x_{i,j}^{DG}$	The value of the reactance associated with the line connecting node i and j in the distribution grid

C. Variables

$\Delta P_{i,t}^{R-up,D}$, $\Delta P_{i,t}^{R-down,D}$	Changes in the RU/RD of flexible demand agent in node i at t
$\Delta P_{i,t}^{R-up,S}$, $\Delta P_{i,t}^{R-down,S}$	Changes in RU/RD of ESS agent in node i at t
$\Delta P_{i,t}^{R-up,G}$, $\Delta P_{i,t}^{R-down,G}$	Changes in RU/RD of CDG agent in node i at t
$\Delta Ramp_{i,t}^{D}$	Changes in ramping of flexible demand agent in node i at t
$\Delta Ramp_{i,t}^{S}$	Changes in ramping of ESS agent in node i at t
$\Delta Ramp_{i,t}^{G}$	Changes in ramping of CDG agent in node i at t
$\Delta P_{i,t}^{Pos,G}$ $\Delta P_{i,t}^{Neg,G}$	Increase/decrease in the generated power by CDGs in node i at t
$\Delta P_{i,t}^{Pos,Dis,S}$ $\Delta P_{i,t}^{Neg,Dis,S}$	Increase/decrease in power-discharging of storages in node i at t
$\Delta P_{i,t}^{Pos,Ch,S}$ $\Delta P_{i,t}^{Neg,Ch,S}$	Increase/decrease in power-charging of storages in node i at t
$DSOC_{i,t}^{S}$	Changes in the state of the charge of storages in node i at t
$LS_{i,t}$	The amount of curtailed Load in node i at t
$Load_{i,t}$	Total amount of power consumption in node i at t
$\alpha_{i,t}^{Ch,S}$, $\alpha_{i,t}^{Dis,S}$	Binary variables determining the charging/discharging states of storages in node i at t
$\Delta P_{i,t}^{Pos,D}$ $\Delta P_{i,t}^{Neg,D}$	Increase/decrease in consumption of demands in node i at t
$\Delta P_{i,t}^{Wind}$	Amount of wind power curtailment in node i at t
$\Delta P_{i,t}^{PV}$	Amount of photovoltaic power curtailment in node i at t
$p_{i,j,t}^{DG,new}$	Active power flow in the line connecting nodes i and j in the distribution grid at t
$P_{i,t}$	Active power exchange in node i at t
$v_{i,t}^{DG}$	Square amount of the voltage in node i in the distribution grid at t
$l_{i,j,t}^{DG}$	Square amount of loading of the line connecting nodes i and j in the distribution grid at t
$Q_{i,j,t}^{DG,new}$	Reactive power flow in line connecting nodes i and j in the distribution grid at t

procurement concept [7]. Respectively, efficient optimization of the LFRs' scheduling should be considered in energy systems with the high amount of VREs to ensure operating the system in a reliable manner. It is noteworthy that alleviating the severe RU/RD of the net electricity demand in distribution grids would smooth the duck curve shape of the net electricity demand, which finally facilitates the increase in the integrated VREs in local energy networks without challenging the load-supply balance and causing high price spikes in power systems.

In recent years, LFRs operated by independent agents have significantly been integrated into distribution grids, which could facilitate their incorporation in supplying required RU/RD services in distribution grids. However, the multi-agent structure of modern systems would limit the complete and direct access of distribution system operators (DSOs) in planning and optimization of the LFRs' scheduling. In other words, DSOs would not play as the operator of LFRs in multi-agent structures. Consequently, DSOs have to deploy efficient management techniques in order to procure RU/RD services from independent agents while ensuring the privacy of their LFRs.

Recently, several research works have strived to consider flexibility constraints while managing the operation of power systems. Respectively, a review of the impacts of flexibility operational services on facilitating the integration of VREs in energy systems is conducted in Ref. [8]. Moreover, the application of LFRs in managing the RU/RD of the distribution grid's net electricity demand is investigated in Refs. [5,7,9–12]. Nevertheless, these research works have not considered the multi-agent distribution systems (MADSs) as well as the operational modeling of distribution grids. Moreover [10,11], have merely considered the central scheduling of LFRs in a microgrid to supply the operational service for alleviating the severe RU/RD in distribution grids. Authors in Ref. [6] have studied the role of electric vehicles in alleviating the duck curve shape of the net electricity demand of the systems with high amount of solar power units. In this paper, a dual objective model is constructed to relieve the severe RU/RD while maximizing the profits of charging stations. As a result, the obtained results in a pareto front show the potential operational points of the system in case of considering the two objective functions in managing the system. Similarly [13], investigates the role of hydrogen production systems to supply flexibility requirements in systems with high amount of integrated VREs. Furthermore, the value of demand-side-management in supplying the operational service in power systems with high amount of integrated VREs is explored in Ref. [14]. The effects of dynamic electricity pricing on flattening the duck curve and increasing the integration of solar units in energy systems are analyzed in Ref. [15]. In this paper, particle swarm optimization modeling is taken into account to study different scenarios in minimizing the VREs curtailment in systems with storage units. Moreover, authors in Ref. [16] have employed dynamic pricing to activate demand response in smart energy systems and flatten the net electricity demand of the system. As discussed, flexibility capacity shortage in systems with high amount of integrated VREs is an important issue that should be addressed with the efficient operation of LFRs and investments in new LFRs. In this regard [17,18], have studied the planning of energy systems with high amount of VREs considering the required energy flexibility. A new methodology is formed in Ref. [19] for activating operational service from structural thermal energy storage units. Moreover, authors in Ref. [20] have studied the energy flexibility of buildings. In this regard, different indices are taken into account to analyze the flexibility of buildings. Reference [21] aims to create a methodology for increasing the on-site VREs in a manufacturing system. Additionally, the proposed method in Ref. [22] investigates the energy flexibility of residential buildings considering the connected storage and electric vehicle units. Furthermore [23,24], have studied modeling demand response in a residential building to enhance the energy flexibility of the system. Nevertheless, the proposed approaches in Refs. [19–24] have not considered the multi-agent arrangement of systems as well as the operational modeling of distribution grids. The proposed models in Refs. [19–24] have merely examined the energy flexibility of one building; while overlooking managing and activating required RU/RD services in an MADS. The paper is added to literature review section of the paper. Reference [25] has focused on investigating the role of the phase change materials in designing the heating system in the buildings, which could provide energy flexibility in the system. However, the focus of this paper is on phase change material optimization and overlooked the RU/RD management in the system. It is noteworthy that the previous studies in the context of activating flexibility RU/RD services to flatten the duce curve shape of the system's net electricity demand have discussed the importance of creating efficient managing models to be applied in local energy systems. Nevertheless, as pointed out, an efficient methodology that could handle the severe RU/RD in MADSs has not yet studied in previous studies.

Flexibility markets could be considered to facilitate exchanging RU/RD services between DSO and independently operated LFRs. Nevertheless, while there are research works that have considered flexibility markets, there is not any commercially matured market, which is being operated in distribution grids and could be extended to model flexibility RU/RD markets. Furthermore, conducting these flexibility RU/RD markets in distribution grids could compromise the competition based upon the lack of liquidity in the system. Accordingly, this paper strives to expand an incentive-based strategy that could motivate the collaboration of independently operated LFRs in the reliable and flexible operation of the system. In other words, based on the above discussion, utilizing incentive-based control models in order to revise the operational planning of LFRs to flatten the duck curve net electricity demand and its associated severe RU/RD seems to be an applicable approach in MADSs. It is noteworthy that the field studies in the context of operational service activation in distribution grids show the effectiveness of the incentive-based concept [26]. In this regard, authors in Ref. [27] have employed the incentive-based control technique to model the interaction between the wind power aggregator and the demand loads. Note that the proposed model has utilized the Stackelberg game to address the stochastic behavior of wind power aggregators by utilizing the demand response service. Authors in Ref. [28] have modeled the coordination of resources in an integrated electricity and heat system by Stackelberg game to manage the condition of the system after a contingency incidence. Furthermore, the coordination of VREs and balancing group resources is modeled by the Stackelberg game in Ref. [29]. The optimization models in Refs. [28,29] have been constructed based on bi-level-problems, which are eventually recast into one-level optimizing formulation by the Karush-Kuhn-Tucker technique to determine the equilibrium point of the models. Furthermore, the Stackelberg game is deployed in Ref. [30] to coordinate the operation of the utility system and the production system for optimizing the costs of both entities. In Ref. [31], the interaction between an integrated energy operator and the local users is modeled by the Stackelberg game. In this paper, the integrated energy operator as the leading entity strives to maximize its profits by optimizing the

Table 1
Comparison of research works in the context of RU/RD management in distribution grids.

Ref. Num.	Flexibility Management	Ramp Management	Modeling Multi-Agent System	Network Modeling	Modeling Different Types of Flexible Resources
[5]	✓	✓		✓	✓
[6]	✓	✓			
[7]	✓	✓			
[9]	✓	✓			✓
[10]	✓	✓			✓
[11]	✓	✓		✓	✓
[12]	✓	✓			✓
[13]	✓	✓			
[14]	✓	✓			✓
[16]	✓	✓	✓		✓
[20]	✓				✓
[21]	✓				
[22]	✓				✓
[23,24]	✓				
[26]	✓		✓	✓	
[27]	✓		✓		
[29]	✓		✓		✓
This paper	✓	✓	✓	✓	✓

scheduling of VREs, while users as follower entities strive to optimize their costs by revising their power consumption. Reference [32] has constructed a bi-level-problem for integrated energy systems to optimize the interaction of the central energy generation unit as well as the heating cost of the customers. In this regard, the upper level aims to maximize the profit of the system while the lower level strives to optimize the heat costs of customers. The optimization of the bus routes and energy allocation in a multi-microgrid system is studied in Ref. [33]. In this paper, a Stackelberg game considering a single leading entity (i.e. bus operator) and multi-follower entities (i.e. microgrids) is deployed in order to optimize the routes of electric buses as well as the power allocation in microgrids. Furthermore, the interaction between the energy hub, load aggregators, and the resident users is modeled by the Stackelberg game in Ref. [34] in order to determine the optimal operational point of future energy networks.

Based on the above discussions, a comparison between research works in the context of RU/RD management in distribution grids is presented in Table 1.

Despite various research studies that have analyzed the efficient operation of distribution grids, managing the severe RU/RD in net electricity demands of MADSs has not yet been thoroughly investigated in previously proposed models. In this context, previous studies have merely focused on the RU/RD management of one entity [9–11] or neglected the distribution grid operational modeling in their proposed models [5–7,9,12,15,16]. Based on the aforementioned points, this paper intends to construct an operational strategy to facilitate the management of RU/RD in MADSs. In this regard, a bi-level-problem based on the Stackelberg game concept is employed in order to model the operational objectives of the DSO and independent agents in the system while managing the severe RU/RD in an efficient manner. Accordingly, the proposed strategy facilitates the contribution of independently operated LFRs in mitigating the severe RU/RD in distribution grids, which would ultimately improve the reliability and flexibility of the system. In other words, while the increasing amount of integrated VREs in MADSs could cause severe RU/RD in the system's net electricity demand, the proposed approach enables the DSO to manage the severe RU/RD by activating flexibility services from LFRs. In the proposed strategy, DSO offers incentives (i.e. bonus) to agents in case of their contribution in the RU/RD management. Consequently, the exchanged-information of agents with the DSO is restricted to the accumulated power deviation and incentives, which would address the privacy concerns of the LFRs. In this strategy, DSO acts as the leading entity to manage the RU/RD of the MADS's net electricity demand, while the agents as follower entities strive to maximize their profits. Note that while [27–32] merely strive to manage the demand flexibility utilizing the Stackelberg game; this paper creates an efficient strategy for ramping management in MADSs. In this regard, the control signals in Refs. [27–32] are corresponding with the power requests of follower entities, while this paper models the effects of the power request by each agent on the RU/RD associated with the overall system's net electricity demand. Respectively, a re-formulation methodology is defined in order to relieve the non-linear terms associated with the RU/RD modeling in the preliminary bi-level-problem. Moreover, the proposed model in this paper considers the operating constraints of the grid, which is overlooked in the proposed models in Refs. [15,16,27,and32]]. In addition, the proposed bi-level-problem is converted into a one-level optimizing formulation taking into account the strong duality concept for better computing efficiency. Note that the non-linear terms in the optimization formulations are linearized in two stages to form a convex model that would converge to the optimal point of the proposed mathematical problem. Finally, in this paper, a stepwise procedure is constructed to achieve the equilibrium point of the severe RU/RD management problem. Accordingly, this procedure facilitates considering the potential rebound effects of energy limited resources, while optimizing the LFRs' re-scheduling in the RU/RD management strategy. It is noteworthy that while most of the previous works have merely studied one type of LFRs in their proposed models; this paper considers different types of available LFRs for re-dispatching, i.e. conventional distributed generations (CDGs), energy storage systems (ESSs), and demands, in order to prepare a generalized strategy and investigate their application in RU/RD management of the system. Furthermore, sensitivity analysis is implemented in this paper to examine the benefits of the proposed methodology in the efficient management of the severe RU/RD in MADSs. Finally, it is noteworthy that incorporating the LFRs to mitigate the severe RU/RD in distribution grids and flatten the net electricity demand would eventually enhance the flexibility of the power network and stabilize the operation of the system [11,12].

In this paper, modeling of MADSs for implementing the RU/RD management approach is discussed in Section III. A. Moreover, the utilized strategy for RU/RD management in the system is illustrated in Section III. B. In this regard, the mathematical modeling of the optimization models employed by the DSO and agents to respectively minimize/maximize their costs/profits in the proposed strategy is presented in Section III. C. The optimization models are based on the Stackelberg game proposed in Section III. B. The transformation of the original problem into a one-level optimizing formulation and the procedure for implementing the RU/RD management strategy in the system are illustrated in Section III. D. Moreover, the results of implementing the RU/RD management procedure on the test system are presented in Section IV. Finally, Section V presents the concluding points of the paper.

2. Methodology

2.1. System modeling

Modern distribution grids could be modeled as multi-agent systems, where each agent schedules its resources independently. In MADSs, system agents align with maximizing their profits could also collaborate in the management of the system by supplying the operational services based upon the DSO's requests. Finally, the privacy concerns associated with the central control of local resources could be addressed by incorporating well-organized management procedures associated with MADSs. A simplified model of the conceived MADS to study the severe RU/RD management is presented in Fig. 1. In this paper, without loss of generality, it is assumed that each agent of the system merely operates one kind of LFRs, e.g. ESSs, flexible load demand, and CDGs. This assumption facilitates the study of the role of each kind of LFRs in mitigating the high RU/RD of the MADS's net electricity demand. Nevertheless, it is noteworthy that the proposed strategy could also effortlessly be adopted in a system where each entity operates different kinds of LFRs; e.g. multiple-microgrid systems.

2.2. Proposed Bi-level methodology

As noted earlier, DSO as a mediator entity between the system's agents and the transmission network aims to efficiently manage the severe RU/RD associated with the distribution grid's net electricity demand by utilizing the local flexibility capacity. As a result, DSO has to revise the preliminary scheduling of LFRs to flatten the net electricity demand of the MADS and address its associated severe RU/RD. In this regard, similar to Refs. [5–13], it is assumed that DSO has to employ an efficient procedure to manage the re-scheduling of LFRs in a way that the MADS's net electricity demand variation in each time interval meets the available flexibility capacity. In this context, while demand/VREs curtailment could be taken into account to optimize the RU/RD in the MADS and flatten the system's net electricity demand; in the proposed strategy, DSO strives to facilitate the contribution of LFRs in the RU/RD management procedure by deploying an incentive-based procedure. Accordingly, DSO would offer incentives (i.e. bonus) to agents of the system to revise their resource re-scheduling in a way that mitigates the severe RU/RD of the MADS′ net electricity demand. Furthermore, the Stackelberg game concept is employed to construct the bi-level problem, where DSO acts as the leading entity and independent agents act as the follower entities. Moreover, the strong duality concept is deployed to facilitate the transformation of the original problem into a one-level optimizing formulation, which enables identifying the equilibrium point; i.e. optimum offered incentives and the agents' re-scheduling.

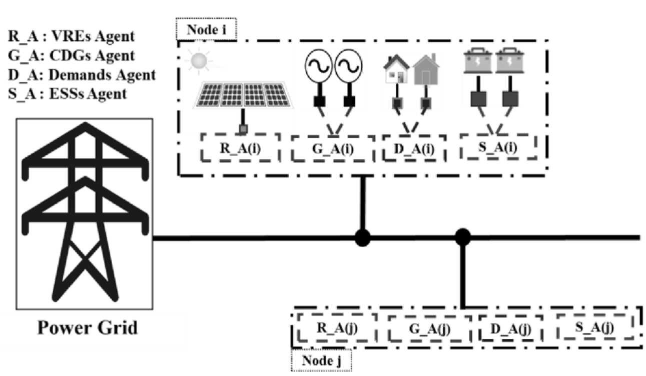

Fig. 1. The considered MADS to study the RU/RD management strategy.

2.3. Bi-level problem

As mentioned earlier, after the day-ahead scheduling of local sources by each agent, DSO aims to induce re-scheduling of independent agents to mitigate the severe RU/RD in the MADS's net electricity demand. Note that this procedure could supply the flexibility RU/RD services to the power network and stabilize its operation. In this regard, it is assumed that DSO would pay the bonus (i.e. $b^{Agent} \times \Delta P^{Ramp,Agent}$) to the system's agent to activate flexibility RU/RD services in MADSs; which would ensure that the variation in the MADS's net electricity demand at each time period meets the available flexibility capacity that could be supplied by the bulk generation units in the transmission grid. Accordingly, this optimization problem is formed as a Stackelberg game where DSO and agents follow their respective operational objectives. Respectively, the optimizations conducted by each entity of the system are formulated in the following sub-sections. It is noteworthy that b^{R-up} shows the incentive signals offered by the DSO to motivate the agents' collaboration in the RU management process. Similarly, b^{R-down} would be offered to agents that contribute in decreasing the high RD in the system. It should be taken into account that the exchanged information between each agent and the DSO is restricted to the offered incentive signals and possible deviation in the agent's day-ahead scheduling. In this respect, without loss of generality, it is considered that agents could participate in the intraday market, in which the market prices associated with purchasing/selling power from/to the upper network are respectively presented by R_t^{up}/ R_t^{down}. In addition, it is assumed that the agent would pay $R_t^{up} \times \Delta P^{Agent}$ in case that its power request is increased or its power generation is reduced; while, the agent would be paid based on $R_t^{down} \times \Delta P^{Agent}$ in case of the decrease in its power request or the increase in its power production. Based on these assumptions, it is noteworthy that market prices and offered incentive signals are positive in all time steps. Nevertheless, the optimization formulations are formulated in a general way; therefore, the proposed approach could be employed in different operational conditions of the grid to procure RU/RD services from the LFRs. Note that the proposed strategy addresses the multi-agent arrangement of the MADSs; i.e. modeling the independent operation of LFRs by considering the power exchange with the upper network, while they supply the operational service based on the received incentives from the DSO.

1) Flexible Demands Optimization:

Optimal re-scheduling optimization of agents responsible for managing flexible load demands is formulated as follows:

$$\text{Max Profit}_i^D = \sum_{t \in T} \begin{pmatrix} \mathrm{b}_{i,t}^{R-up,D} \Delta P_{i,t}^{R-up,D} + \\ \mathrm{b}_{i,t}^{R-down,D} \Delta P_{i,t}^{R-down,D} \\ -R_t^{up} \Delta P_{i,t}^{Pos,D} + \\ R_t^{down} \Delta P_{i,t}^{Neg,D} \end{pmatrix} \tag{1a}$$

Subject to

$$0 \le \Delta P_{i,t}^{Pos,D} \le \Delta P_{i,t}^{Max,Pos,D}, \qquad t \in T \tag{1b}$$

$$0 \le \Delta P_{i,t}^{Neg,D} \le \Delta P_{i,t}^{Max,Neg,D}, \qquad t \in T \tag{1c}$$

$$\sum_t \left(\Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D} \right) = 0, \qquad t \in T \tag{1d}$$

$$\begin{cases} \Delta P_{i,t}^{R-up,D} = -\left(\Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D}\right) + \left(\Delta P_{i,t-1}^{Pos,D} - \Delta P_{i,t-1}^{Neg,D}\right) & \left(\Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D}\right) - \left(\Delta P_{i,t-1}^{Pos,D} - \Delta P_{i,t-1}^{Neg,D}\right) \le 0 \\ \Delta P_{i,t}^{R-down,D} = \left(\Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D}\right) - \left(\Delta P_{i,t-1}^{Pos,D} - \Delta P_{i,t-1}^{Neg,D}\right) & \left(\Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D}\right) - \left(\Delta P_{i,t-1}^{Pos,D} - \Delta P_{i,t-1}^{Neg,D}\right) \ge 0 \end{cases} \tag{1e}$$

The optimization problem intends to maximize the profit of the i_{th} agent in (1a) considering the incentive signals as well as the costs associated with power re-scheduling of flexible demands. Moreover, (1b)-(1d) impose limitations over the increasing/decreasing as well as the total changes in the energy requests of load demands. Finally, $\mathrm{b}_{i,t}^{R-up,D}$ and $\mathrm{b}_{i,t}^{R-down,D}$ are constant parameters announced by the DSO as incentive signals to revise the scheduling of load demands. Therefore, (1e) is taken into account to ensure that the agent would receive the incentive when its RU/RD changes would benefit the system; otherwise, the agent would not receive the incentive for its RU/RD changes. This formulation facilitates separating the RU and RD services supplied by the demand agents. In this regard, in case that the agent supplies the RU/RD services required by the DSO, it would receive the bonus to compensate its operational costs. Note that at each time interval based on the net electricity demand of the system and the ramp-service required by the DSO, only one of the bonus signals (i.e. $\mathrm{b}_{i,t}^{R-up,D}$, and $\mathrm{b}_{i,t}^{R-down,D}$) could be higher than zero.

2) Storage Energy Systems Optimization:

The optimization associated with maximizing the profit of agents responsible for the operation of ESSs while participating in the proposed severe RU/RD mitigation strategy is formulated as follows:

$$\text{Max Profit}_i^S = \sum_{t \in T} \begin{pmatrix} \mathrm{b}_{i,t}^{R-up,S} \Delta P_{i,t}^{R-up,S} + \\ \mathrm{b}_{i,t}^{R-down,S} \Delta P_{i,t}^{R-down,S} \\ -R_t^{up} \Delta P_{i,t}^{Pos,Ch,S} + \\ R_t^{down} \Delta P_{i,t}^{Neg,Ch,S} + \\ R_t^{down} \Delta P_{i,t}^{Pos,Dis,S} \\ -R_t^{up} \Delta P_{i,t}^{Neg,Dis,S} \end{pmatrix} \tag{2a}$$

Subject to

$$0 \le \Delta P_{i,t}^{Pos,Ch,S} \le \Delta P_{i,t}^{Max,Pos,Ch,S}, \qquad t \in T \tag{2b}$$

$$0 \le \Delta P_{i,t}^{Neg,Ch,S} \le \Delta P_{i,t}^{Max,Neg,Ch,S}, \qquad t \in T \tag{2c}$$

$$0 \le \Delta P_{i,t}^{Pos,Dis,S} \le \Delta P_{i,t}^{Max,Pos,Dis,S}, \qquad t \in T \tag{2d}$$

$$0 \le \Delta P_{i,t}^{Neg,Dis,S} \le \Delta P_{i,t}^{Max,Neg,Dis,S}, \qquad t \in T \tag{2e}$$

$$DSOC_{i,t+1}^S = DSOC_{i,t}^S + \frac{1}{E_i^S} \times \begin{pmatrix} \eta_i^{Ch,S}\left(\Delta P_{i,t}^{Pos,Ch,S} - \Delta P_{i,t}^{Neg,Ch,S}\right) - \\ \left(\Delta P_{i,t}^{Pos,Dis,S} - \Delta P_{i,t}^{Neg,Dis,S}\right) \Big/ \eta_i^{Dis,S} \end{pmatrix}, \qquad t \in T \tag{2f}$$

$$DSOC_{i,t}^{Min,S} \le DSOC_{i,t}^S \le DSOC_{i,t}^{Max,S}, \qquad t \in T \tag{2g}$$

$$\begin{cases} \Delta P_{i,t}^{R-up,S} = -\left[\begin{array}{c}\left(\begin{array}{c}\Delta P_{i,t}^{Pos,Ch,S}- \\ \Delta P_{i,t}^{Neg,Ch,S}\end{array}\right)- \\ \left(\begin{array}{c}\Delta P_{i,t}^{Pos,Dis,S}- \\ \Delta P_{i,t}^{Neg,Dis,S}\end{array}\right)\end{array}\right] + \left[\begin{array}{c}\left(\Delta P_{i,t-1}^{Pos,Ch,S} - \Delta P_{i,t-1}^{Neg,Ch,S}\right)- \\ \left(\Delta P_{i,t-1}^{Pos,Dis,S} - \Delta P_{i,t-1}^{Neg,Dis,S}\right)\end{array}\right] & \left[\begin{array}{c}\left(\begin{array}{c}\Delta P_{i,t}^{Pos,Ch,S}- \\ \Delta P_{i,t}^{Neg,Ch,S}\end{array}\right)- \\ \left(\begin{array}{c}\Delta P_{i,t}^{Pos,Dis,S}- \\ \Delta P_{i,t}^{Neg,Dis,S}\end{array}\right)\end{array}\right] - \left[\begin{array}{c}\left(\begin{array}{c}\Delta P_{i,t-1}^{Pos,Ch,S}- \\ \Delta P_{i,t-1}^{Neg,Ch,S}\end{array}\right)- \\ \left(\begin{array}{c}\Delta P_{i,t-1}^{Pos,Dis,S}- \\ \Delta P_{i,t-1}^{Neg,Dis,S}\end{array}\right)\end{array}\right] \leq 0 \\ \Delta P_{i,t}^{R-down,S} = \left[\begin{array}{c}\left(\begin{array}{c}\Delta P_{i,t}^{Pos,Ch,S}- \\ \Delta P_{i,t}^{Neg,Ch,S}\end{array}\right)- \\ \left(\begin{array}{c}\Delta P_{i,t}^{Pos,Dis,S}- \\ \Delta P_{i,t}^{Neg,Dis,S}\end{array}\right)\end{array}\right] - \left[\begin{array}{c}\left(\Delta P_{i,t-1}^{Pos,Ch,S} - \Delta P_{i,t-1}^{Neg,Ch,S}\right)- \\ \left(\Delta P_{i,t-1}^{Pos,Dis,S} - \Delta P_{i,t-1}^{Neg,Dis,S}\right)\end{array}\right] & \left[\begin{array}{c}\left(\begin{array}{c}\Delta P_{i,t}^{Pos,Ch,S}- \\ \Delta P_{i,t}^{Neg,Ch,S}\end{array}\right)- \\ \left(\begin{array}{c}\Delta P_{i,t}^{Pos,Dis,S}- \\ \Delta P_{i,t}^{Neg,Dis,S}\end{array}\right)\end{array}\right] - \left[\begin{array}{c}\left(\begin{array}{c}\Delta P_{i,t-1}^{Pos,Ch,S}- \\ \Delta P_{i,t-1}^{Neg,Ch,S}\end{array}\right)- \\ \left(\begin{array}{c}\Delta P_{i,t-1}^{Pos,Dis,S}- \\ \Delta P_{i,t-1}^{Neg,Dis,S}\end{array}\right)\end{array}\right] \geq 0 \end{cases} \tag{2h}$$

In the presented formulation, (2a) as the objective function maximizes the profits of the agent by modeling the received incentive signals and the costs of re-scheduling the exchanging power with the grid. Moreover, (2b)-(2e) restrict the deviation in the power charging/discharging of ESSs, while (2f)-(2g) respectively present the change in the state of the charge of the storage units as well as its limitations. Furthermore, (2h) ensures that the agent would receive incentives in case its ramping changes decrease the high ramping in the system. In this regard, (2h) separates RU and RD services supplied by the storage agent; therefore, the agent would receive the bonus based on the supplied RU/RD services to the DSO.

3) Conventional Distributed Generations Optimization:

Agents responsible for managing CDGs would optimize their rescheduling based upon the received incentives as follows:

$$\text{Max Profit}_i^G = \sum_{t\in T}\left(\begin{array}{l} b_{i,t}^{R-up,G}\Delta P_{i,t}^{R-up,G}+ \\ b_{i,t}^{R-down,G}\Delta P_{i,t}^{R-down,G} \\ -R_t^{up}\Delta P_{i,t}^{Neg,G} + R_t^{down}\Delta P_{i,t}^{Pos,G}+ \\ \left(\Delta P_{i,t}^{Neg,G} - \Delta P_{i,t}^{Pos,G}\right)C_{i,t}^{G} \end{array}\right) \tag{3a}$$

Subject to

$$0 \leq \Delta P_{i,t}^{Pos,G} \leq \Delta P_{i,t}^{Max,Pos,G}, \qquad t\in T \tag{3b}$$

$$0 \leq \Delta P_{i,t}^{Neg,G} \leq \Delta P_{i,t}^{Max,Neg,G}, \qquad t\in T \tag{3c}$$

$$\begin{cases} \Delta P_{i,t}^{R-up,G} = -\left(\Delta P_{i,t}^{Neg,G} - \Delta P_{i,t}^{Pos,G}\right) + \left(\Delta P_{i,t-1}^{Neg,G} - \Delta P_{i,t-1}^{Pos,G}\right) & \left(\Delta P_{i,t}^{Neg,G} - \Delta P_{i,t}^{Pos,G}\right) - \left(\Delta P_{i,t-1}^{Neg,G} - \Delta P_{i,t-1}^{Pos,G}\right) \leq 0 \\ \Delta P_{i,t}^{R-down,G} = \left(\Delta P_{i,t}^{Neg,G} - \Delta P_{i,t}^{Pos,G}\right) - \left(\Delta P_{i,t-1}^{Neg,G} - \Delta P_{i,t-1}^{Pos,G}\right) & \left(\Delta P_{i,t}^{Neg,G} - \Delta P_{i,t}^{Pos,G}\right) - \left(\Delta P_{i,t-1}^{Neg,G} - \Delta P_{i,t-1}^{Pos,G}\right) \geq 0 \end{cases} \tag{3d}$$

The optimization aims to maximize the agent's profits in (3a); whereas (3b) and (3c) are taken into account to restrict the decrease/increase in the power generation by CDGs. Moreover, (3d) is considered to model the condition that the agent would merely receive bonus from the DSO in case of the contribution in decreasing the RU/RD in the MADS. This formulation facilitates separating the RU and RD services supplied by the CDGs. In this regard, in case that the agent supplies the RU/RD service required by the DSO, it would receive the bonus to compensate its operational costs.

4) Optimization Model of the System Operator:

Based upon the proposed strategy, DSO is the responsible unit for managing the RU/RD constraints in MADSs. DSO would be able to propose incentive signals to agents operating LFRs for convincing their re-scheduling or consider VREs/load curtailment to address the RU/RD limitations. Consequently, the optimization problem conducted by the DSO utilizing DistFlow formulation in the convex-form [35,36] for operational modeling of the distribution grid is as follows:

$$\text{Min Cost}^{Ramping\_Service} = \sum_{t\in T}\sum_{i}\left(\begin{array}{l} b_{i,t}^{R-up,D}\Delta P_{i,t}^{R-up,D}+ \\ b_{i,t}^{R-down,D}\Delta P_{i,t}^{R-down,D} \\ +b_{i,t}^{R-up,S}\Delta P_{i,t}^{R-up,S}+ \\ b_{i,t}^{R-down,S}\Delta P_{i,t}^{R-down,S}+ \\ b_{i,t}^{R-up,G}\Delta P_{i,t}^{R-up,G}+ \\ b_{i,t}^{R-down,G}\Delta P_{i,t}^{R-down,G} \\ +C_{i,t}^{VRE}\left(\Delta P_{i,t}^{Wind}+\Delta P_{i,t}^{PV}\right) \\ +C_{i,t}^{LS}LS_{i,t} \end{array}\right) + \text{Cos } t_{Dloss}^{grid} \tag{4a}$$

Subject to (1e), (2h), (3d), and

$$\begin{aligned}\Delta P_{i,t} = {} & \Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D} + \Delta P_{i,t}^{Pos,Ch,S} - \Delta P_{i,t}^{Neg,Ch,S} \\ & +\Delta P_{i,t}^{Neg,Dis,S} - \Delta P_{i,t}^{Pos,Dis,S} + \Delta P_{i,t}^{Neg,G} - \Delta P_{i,t}^{Pos,G} \\ & -\Delta P_{i,t}^{Wind} - \Delta P_{i,t}^{PV} - LS_{i,t}\end{aligned} \tag{4b}$$

$$\begin{aligned} v_{j,t}^{DG} = {} & v_{i,t}^{DG} + 2\left(r_{i,j}^{DG}P_{i,j,t}^{DG,new} + x_{i,j}^{DG}Q_{i,j,t}^{DG,new}\right) \\ & + l_{i,j,t}^{DG}\left(\left(r_{i,j}^{DG}\right)^2 + \left(x_{i,j}^{DG}\right)^2\right)\end{aligned} \tag{4c}$$

$$\sum_j\left(P_{i,j,t}^{DG,new} + l_{i,j,t}^{DG}\cdot r_{i,j}^{DG}\right) = P_{i,t} \tag{4d}$$

$$\sum_j\left(Q_{i,j,t}^{DG,new} + l_{i,j,t}^{DG}\cdot x_{i,j}^{DG}\right) = Q_{i,t} \tag{4e}$$

$$\left(P_{i,j,t}^{DG,new}\right)^2 + \left(Q_{i,j,t}^{DG,new}\right)^2 \le v_{i,t}^{DG}l_{i,j,t}^{DG} \tag{4f}$$

$$v^{Min} \le v_{i,t}^{DG} \le v^{Max} \tag{4g}$$

$$0 \le \Delta P_{i,t}^{Wind} \le \Delta P_{i,t}^{Max,Wind} \tag{4h}$$

$$0 \le \Delta P_{i,t}^{PV} \le \Delta P_{i,t}^{Max,PV} \tag{4i}$$

$$0 \le LS_{i,t} \le Load_{i,t} \tag{4j}$$

$$Load_{i,t} = Load_{i,t}^{Scheduled} + \Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D} \tag{4k}$$

$$P_{i,t} = P_{i,t}^{Scheduled} + \Delta P_{i,t} \tag{4l}$$

$$Ramp^{down,Max} \le P_{i,t} - P_{i,t-1} \le Ramp^{up,Max}, \qquad i = i_0 \tag{4m}$$

The objective (4a) aims to minimize the costs of the incentives offered by the DSO as well as the VREs/load curtailment and the changes in the grid loss due to agents re-scheduling. In this regard, the DSO as the leader entity aims to minimize the costs associated with the severe RU/RD management in the MADS. In this regard, the curtailment of loads/VREs, as well as the re-scheduling of LFRs as options available for addressing the severe RU/RD in the MADS, are considered in the optimization modeling of the DSO. Moreover, (4b) determines the changes in the power exchange with the grid at each node of the distribution grid; while, (4c)-(4g) represent the operational modeling of the distribution grid. Furthermore, (4h) and (4i) show the limitations over the curtailment of wind power and PV units, while (4j) and (4k) determine the maximum amount of the possible load-shedding in each node of the grid. Finally, (4l) and (4 m) are considered for the connecting node of the distribution grid to the upper-level network to model the RU/RD limitations. These constraints define the net electricity demand variability of the MADS seen by the upper-level network, which should be less than a manageable RU/RD. According to Refs. [5,37,38], the ramping limitations could be defined by the system operators based on the system flexibility and the net electricity demand variability. Respectively, application of the proposed strategy could mitigate the severe RU/RD in the MADS's net electricity demand and supply the required flexibility RU/RD services to the network. Moreover, minimizing the RU/RD of the MADS's net electricity demand would flatten the duck curve shape of the net electricity load in energy systems with high amount of solar power units.

Based on the proposed model, the costs associated with the ramping management procedure would be finally compensated by the operator of the upper-level network, which has imposed limitations over the ramping associated with the MADS's net electricity demand. In other words, it is conceived that the MADS would supply the upper-level network with the flexibility ramp-service by considering the limitations over its RU/RD. Moreover, in case that the limitations have been set as a general regulation for the operation of local systems, the agents of the system would finally compensate the associated costs based upon their role in the preliminary severe ramp in the system. Nevertheless, the proposed procedure is structured to be able to efficiently find the optimal re-scheduling of the LFRs in a MADS based on the RU/RD constraints. In this respect, the agents strive to optimize their profits, while DSO considers the offered incentives as well as the costs associated with the changes in the operational condition of the grid in its respective optimization.

In the constructed bi-level incentive-based problem, agents would be responsible for costs associated with revising their resource scheduling, while DSO aims to motivate their collaboration in the severe RU/RD management process by proposing bonus signals. In this regard, in order to determine the equilibrium point of the optimization problem with efficient computation, the one-level mathematical problem with complementarity constraints (MPCC) is extracted from the bi-level-problem [12,27–32]. In this regard, this paper takes advantage of the strong duality concept, which facilitates formulating the MPCC model. Finally, a stepwise procedure is constructed for implementing the MPCC model to mitigate the severe RU/RD in MADSs.

2.4. Constructing the MPCC model

To construct the MPCC model, the constraints of the optimizations conducted by follower agents and their dual equations would be combined with the optimization model of the DSO. This procedure would ensure that the MPCC model would converge to the optimal point of the bi-level-problem [27,39]. However, the constraints (1e), (2h), and (3d) considered in the DSO and agents' optimization models would add non-linear terms (i.e. binary variables) in their respective optimization models, which would finally result in non-convex formulations. In this regard, the optimization models associated with the agents should efficiently be revised to derive convex models. Accordingly, as similar constraints are also included in DSO optimization formulation, constraints (1e), (2h), and (3d) are omitted from the optimization models of agents. Furthermore, in order to ensure that omitting (1e), (2h), and (3d) from the agents' optimization models would not change the optimal response of the bi-level problem, the DSO's optimization is formulated as follows:

$$\text{Min Cost}^{Ramping\_Service} = \sum_{t\in T}\sum_{i}\begin{pmatrix} b_{i,t}^{R-up,D}\left(-\Delta Ramp_{i,t}^{D}\right)+ \\ b_{i,t}^{R-down,D}\Delta Ramp_{i,t}^{D} \\ +b_{i,t}^{R-up,S}\left(-\Delta Ramp_{i,t}^{S}\right)+ \\ b_{i,t}^{R-down,S}\Delta Ramp_{i,t}^{S}+ \\ b_{i,t}^{R-up,G}\left(-\Delta Ramp_{i,t}^{G}\right)+ \\ b_{i,t}^{R-down,G}\Delta Ramp_{i,t}^{G} \\ +C_{i,t}^{VRE}\left(\Delta P_{i,t}^{Wind}+\Delta P_{i,t}^{PV}\right) \\ +C_{i,t}^{LS}LS_{i,t} \end{pmatrix} + \text{Cos}\ t_{Dloss}^{grid} \tag{5a}$$

Subject to (4b)-(4l), and

$$b_{i,t}^{R-up,D}\left(-\Delta Ramp_{i,t}^{D}\right) \geq 0 \tag{5b}$$

$$b_{i,t}^{R-down,D}\Delta Ramp_{i,t}^{D} \geq 0 \tag{5c}$$

$$b_{i,t}^{R-up,S}\left(-\Delta Ramp_{i,t}^{S}\right) \geq 0 \tag{5d}$$

$$b_{i,t}^{R-down,S}\Delta Ramp_{i,t}^{S} \geq 0 \tag{5e}$$

$$b_{i,t}^{R-up,G}\left(-\Delta Ramp_{i,t}^{G}\right) \geq 0 \tag{5f}$$

$$b_{i,t}^{R-down,G}\Delta Ramp_{i,t}^{G} \geq 0 \tag{5g}$$

$$\Delta Ramp_{i,t}^{D} = \left(\Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D}\right) - \left(\Delta P_{i,t-1}^{Pos,D} - \Delta P_{i,t-1}^{Neg,D}\right) \tag{5h}$$

$$\Delta Ramp_{i,t}^{S} = \begin{bmatrix} \left(\Delta P_{i,t}^{Pos,Ch,S} - \Delta P_{i,t}^{Neg,Ch,S}\right) - \\ \left(\Delta P_{i,t}^{Pos,Dis,S} - \Delta P_{i,t}^{Neg,Dis,S}\right) \end{bmatrix} - \begin{bmatrix} \left(\Delta P_{i,t-1}^{Pos,Ch,S} - \Delta P_{i,t-1}^{Neg,Ch,S}\right) - \\ \left(\Delta P_{i,t-1}^{Pos,Dis,S} - \Delta P_{i,t-1}^{Neg,Dis,S}\right) \end{bmatrix} \tag{5i}$$

$$\Delta Ramp_{i,t}^{G} = \left(\Delta P_{i,t}^{Neg,G} - \Delta P_{i,t}^{Pos,G}\right) - \left(\Delta P_{i,t-1}^{Neg,G} - \Delta P_{i,t-1}^{Pos,G}\right) \tag{5j}$$

$$b_{i,t}^{R-up,D}, b_{i,t}^{R-down,D}, b_{i,t}^{R-up,S}, b_{i,t}^{R-down,S}, b_{i,t}^{R-up,G}, b_{i,t}^{R-down,G} \geq 0 \tag{5k}$$

In this formulation, (5b)-(5g) are considered to ensure that each agent would merely receive the bonus when its ramping changes benefit the system. Note that the bonus received by flexible demand agents, ESSs, and CDGs would similarly be changed in their optimization models. In this regard, in case the agent's ramping changes would not benefit the system, its associated bonus would be set to zero. As a result, reformulation of the optimization problems associated with DSO and agents based on the assumption of conducting the optimization in one-level through the MPCC model has resulted in deriving convex form formulations which would ensure convergence to the optimal response of the original bi-level incentive-based problem.

Based on the aforementioned formulation and assumptions, the optimization conducted by the demand agent is modeled as below:

$$\text{Max Profit}_{i}^{D} = \sum_{t\in T}\begin{pmatrix} b_{i,t}^{R-up,D}\left(-\begin{pmatrix}\left(\Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D}\right) - \\ \left(\Delta P_{i,t-1}^{Pos,D} - \Delta P_{i,t-1}^{Neg,D}\right)\end{pmatrix}\right) + \\ b_{i,t}^{R-down,D}\begin{pmatrix}\left(\Delta P_{i,t}^{Pos,D} - \Delta P_{i,t}^{Neg,D}\right) - \\ \left(\Delta P_{i,t-1}^{Pos,D} - \Delta P_{i,t-1}^{Neg,D}\right)\end{pmatrix} \\ -R_{t}^{up}\Delta P_{i,t}^{Pos,D}+ \\ R_{t}^{down}\Delta P_{i,t}^{Neg,D} \end{pmatrix} \tag{6a}$$

Subject to (1b) − (1d).

Similarly, the optimization of ESSs agents could be reformulated as follows:

$$\text{Max Profit}_{i}^{S} = \sum_{t\in T}\begin{pmatrix} b_{i,t}^{R-up,S}\left(-\Delta Ramp_{i,t}^{S}\right)+ \\ b_{i,t}^{R-down,S}\Delta Ramp_{i,t}^{S}+ \\ -R_{t}^{up}\Delta P_{i,t}^{Pos,Ch,S}+ \\ R_{t}^{down}\Delta P_{i,t}^{Neg,Ch,S}+ \\ R_{t}^{down}\Delta P_{i,t}^{Pos,Dis,S} \\ -R_{t}^{up}\Delta P_{i,t}^{Neg,Dis,S} \end{pmatrix} \tag{7a}$$

Subject to (2b)-(2g) and (5i).

In a similar way, the optimization associated with the agents operating CDGs could be also formulated as follows:

$$\text{Max Profit}_{i}^{G} = \sum_{t\in T}\begin{pmatrix} b_{i,t}^{R-up,G}\left(-\Delta Ramp_{i,t}^{G}\right)+ \\ b_{i,t}^{R-down,G}\Delta Ramp_{i,t}^{G} \\ -R_{t}^{up}\Delta P_{i,t}^{Neg,G} + R_{t}^{down}\Delta P_{i,t}^{Pos,G}+ \\ \left(\Delta P_{i,t}^{Neg,G} - \Delta P_{i,t}^{Pos,G}\right)C_{i,t}^{G} \end{pmatrix} \tag{8a}$$

Subject to (3b) − (3c) and (5j).

As mentioned, the convex optimization in (5) − (8) are formulated considering the transformation of the bi-level-problem into a one-level-optimizing-formulation to determine the optimal point of the proposed strategy. The new formulations have relieved the non-linear terms associated with the RU/RD services in optimization models (1)–(4). In this regard, in case that the changes in the ramping of an agent at time interval t do not supply the operational service required by the DSO; based on (5b)-(5g), the offered bonus signal to the respective agent would be assigned to zero. Respectively, the non-linear constraints (1e), (2h), and (3d) are relieved considering the point that optimizations of the DSO and agents would be solved simultaneously in the MPCC model.

Consequently, the derived MPCC model of the optimization problems in (5) − (8) is formulated in (9). Note that based on the strong duality concept, the constraints of optimizations conducted by agents and their dual equations are combined with the optimization model of the leading entity to derive the MPCC model [27,39]. In other words, modeling the constraints of the optimizations associated with the agents and their dual equations as well as the strong duality condition associated with the agents' optimization objectives would ensure finding the optimal point of the bi-level problem [40].

$$\text{Min Cost}^{Ramping\_Service} \tag{9a}$$

Subject to (1b)-(1d), (2b)-(2g), (3b)-(3c), (4b)-(4l), (5b)-(5k) and

$$\begin{aligned}\lambda_{i,t}^{Pos,D}+\lambda_i^{EDemand}\geq\ & b_{i,t}^{R-down,D}-b_{i,t+1}^{R-down,D}\\ &-b_{i,t}^{R-up,D}+b_{i,t+1}^{R-up,D}-R_t^{up}\end{aligned} \tag{9b}$$

$$\begin{aligned}\lambda_{i,t}^{Neg,D}-\lambda_i^{EDemand}\geq\ & b_{i,t}^{R-up,D}-b_{i,t+1}^{R-up,D}\\ &-b_{i,t}^{R-down,D}+b_{i,t+1}^{R-down,D}+R_t^{down}\end{aligned} \tag{9c}$$

$$\sum_{t\in T}\begin{pmatrix}\lambda_{i,t}^{Pos,D}\times\Delta P_{i,t}^{Max,Pos,D}+\\ \lambda_{i,t}^{Neg,D}\times\Delta P_{i,t}^{Max,Neg,D}\end{pmatrix}=\text{Profit}_i^D \tag{9d}$$

$$\lambda_{i,t}^{SOC}-\lambda_{i,t+1}^{SOC}+\lambda_{i,t}^{SOC,Max}-\lambda_{i,t}^{SOC,Min}=0 \tag{9e}$$

$$\begin{aligned}\lambda_{i,t}^{SOC}\times\frac{-\eta_i^{Ch,S}}{E_i^S}+\lambda_{i,t}^{Ch,Pos}\geq\ & b_{i,t}^{R-down,S}-b_{i,t+1}^{R-down,S}\\ &-b_{i,t}^{R-up,S}+b_{i,t+1}^{R-up,S}-R_t^{up}\end{aligned} \tag{9f}$$

$$\begin{aligned}\nu_{i,t}^{SOC}\times\frac{\eta_i^{Ch,S}}{E_i^S}+\lambda_{i,t}^{Ch,Neg}\geq\ & b_{i,t}^{R-up,S}-b_{i,t+1}^{R-up,S}\\ &-b_{i,t}^{R-down,S}+b_{i,t+1}^{R-down,S}+R_t^{down}\end{aligned} \tag{9g}$$

$$\begin{aligned}\lambda_{i,t}^{SOC}\times\frac{1}{\eta_i^{Dis,S}E_i^S}+\lambda_{i,t}^{Dis,Pos}\geq\ & b_{i,t}^{R-up,S}-b_{i,t+1}^{R-up,S}\\ &-b_{i,t}^{R-down,S}+b_{i,t+1}^{R-down,S}+R_t^{down}\end{aligned} \tag{9h}$$

$$\begin{aligned}\lambda_{i,t}^{SOC}\times\frac{-1}{\eta_i^{Dis,S}E_i^S}+\lambda_{i,t}^{Dis,Neg}\geq\ & b_{i,t}^{R-down,S}-b_{i,t+1}^{R-down,S}\\ &-b_{i,t}^{R-up,S}+b_{i,t+1}^{R-up,S}-R_t^{up}\end{aligned} \tag{9i}$$

$$\sum_{t\in T}\begin{pmatrix}\lambda_{i,t}^{Ch,Pos}\times\Delta P_{i,t}^{Max,Pos,Ch,S}+\\ \lambda_{i,t}^{Ch,Neg}\times\Delta P_{i,t}^{Max,Neg,Ch,S}+\\ \lambda_{i,t}^{Dis,Pos}\times\Delta P_{i,t}^{Max,Pos,Dis,S}+\\ \lambda_{i,t}^{Dis,Neg}\times\Delta P_{i,t}^{Max,Neg,Dis,S}\\ +\lambda_{i,t}^{SOC,Max}\times DSOC_{i,t}^{Max,S}-\\ \lambda_{i,t}^{SOC,Min}\times DSOC_{i,t}^{Min,S}\end{pmatrix}=\text{Profit}_i^S \tag{9j}$$

$$\sum_{t\in T}\left(\lambda_{i,t}^{Pos,G}\Delta P_{i,t}^{Max,Pos,G}+\lambda_{i,t}^{Neg,G}\Delta P_{i,t}^{Max,Neg,G}\right)=\text{Profit}_i^G \tag{9k}$$

$$\begin{aligned}&\lambda_{i,t}^{Pos,G}\geq b_{i,t}^{R-up,G}-b_{i,t+1}^{R-up,G}\\ &-b_{i,t}^{R-down,G}+b_{i,t+1}^{R-down,G}+R_t^{down}-C_{i,t}^G\end{aligned} \tag{9l}$$

$$\begin{aligned}&\lambda_{i,t}^{Neg,G}\geq b_{i,t}^{R-down,G}-b_{i,t+1}^{R-down,G}\\ &-b_{i,t}^{R-up,G}+b_{i,t+1}^{R-up,G}-R_t^{up}+C_{i,t}^G\end{aligned} \tag{9m}$$

$$\begin{aligned}&0\leq P_{i,t}^{Scheduled,Ch,S}+\Delta P_{i,t}^{Pos,Ch,S}-\\ &\Delta P_{i,t}^{Neg,Ch,S}\leq P_{i,t}^{Max,Ch,S}\cdot\alpha_{i,t}^{Ch,S}\end{aligned} \tag{9n}$$

$$\begin{aligned}&0\leq P_{i,t}^{Scheduled,Dis,S}+\Delta P_{i,t}^{Pos,Dis,S}-\\ &\Delta P_{i,t}^{Neg,Dis,S}\leq P_{i,t}^{Max,Dis,S}\cdot\alpha_{i,t}^{Dis,S}\end{aligned} \tag{9o}$$

$$\alpha_{i,t}^{Ch,S}+\alpha_{i,t}^{Dis,S}\leq 1 \tag{9p}$$

In the MPCC formulation, (9b)-(9d), (9e)-(9j), and (9k)-(9 m) are respectively utilized to present the dual model associated with the optimization problems of agents operating flexible load demands, ESSs, and CDGs. Respectively $\lambda_{i,t}^{Pos,D}$ $\lambda_{i,t}^{Neg,D}$ $\lambda_i^{EDemand}$ $\lambda_{i,t}^{Ch,Pos}$, $\lambda_{i,t}^{Ch,Neg}$, $\lambda_{i,t}^{Dis,Pos}$ $\lambda_{i,t}^{Dis,Neg}$ $\lambda_{i,t}^{SOC}$ $\lambda_{i,t}^{SOC,Max}$ $\lambda_{i,t}^{SOC,Min}$, $\lambda_{i,t}^{Pos,G}$, and $\lambda_{i,t}^{Neg,G}$ are Lagrangian multipliers associated with (1b)-(1d), (2b)-(2g), and (3b)-(3c). It is noteworthy that (9d), (9j), and (9k) model the strong duality conditions, which indicates that, in the optimal point, the value of the objectives associated with the agent's optimizations would be equal to the objective value of their dual models [40]. Furthermore, (9n)-(9p) are taken into account to ensure that ESSs would be merely scheduled in one operating mode (i.e. charging or discharging) at each time interval.

2.5. Implementation of the MPCC formulation for mitigating the severe ramping in the MADS

Based on the proposed strategy, DSO would offer incentive signals to system agents in case that their resource scheduling would benefit the severe RU/RD mitigation. Consequently, the bonus signals would be merely offered at time intervals that the system is confronting with the severe RU/RD. As a result, the type of offered bonus signal at each time interval could be determined with regard to the net electricity demand of the MADS. Nevertheless, rescheduling of energy-limited resources based on the received bonus signals could cause ramping issues at other time periods due to the rebound effect. Consequently, besides intense ramping caused by preliminary scheduling of resources, rebound effects should also be taken into consideration while implementing the proposed approach in MADSs. Accordingly, the stepwise procedure, presented in Fig. 2, is created in this paper to optimize the ramping management in the system while considering the potential rebound effects caused by re-scheduling of energy-limited resources.

The proposed strategy for ramping management would be conducted by DSO to optimize the re-scheduling of LFRs in an efficient manner. Accordingly, DSO would receive the maximum total deviation from the preliminary day-ahead scheduling of each agent to construct the MPCC model and apply the stepwise procedure shown in Fig. 2. In this regard, each agent would merely announce its accumulated possible deviation from the day-ahead scheduled point to the DSO without broadcasting the scheduled operational point of each of the local resources, which would address the privacy concerns associated with multi-agent structures. Respectively, DSO would receive the accumulated possible deviation from the preliminary scheduling of agents, which would facilitate securing the operational point of each of the local resources. That is why the optimization formulation and the stepwise procedure shown in Fig. 2 for mitigating the severe ramping would ensure addressing the privacy concerns of local resources. Furthermore, the non-linearity in the MPCC model caused by non-linear terms $b^{Agent} \times \Delta Ramp^{Agent}$ is resolved by taking into account the SOS2 method [39]. In this regard, the complete MPCC model which is applied to determine the optimal point of the bi-level problem is presented in Ref. [41].

3. Case study

In this section, the proposed strategy is applied to the IEEE-37 bus test system [42], represented in Fig. 3, to analyze its application in optimal RU/RD management in MADSs. In this regard, similar to previous research works in the context of severe RU/RD management of energy systems, it is conceived that the network is balanced and each node of the grid would have different agents to operate their respective LFRs (i.e. CDGs, loads, and ESSs). Respectively, the operational characteristics of the demand and resources as well as the grid are adapted from Refs. [43,44,47] and presented

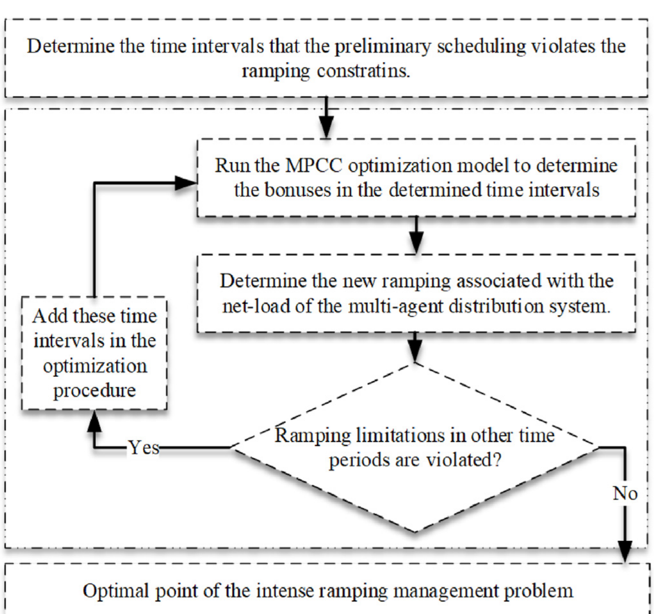

Fig. 2. The proposed stepwise procedure utilized to implement the MPCC model.

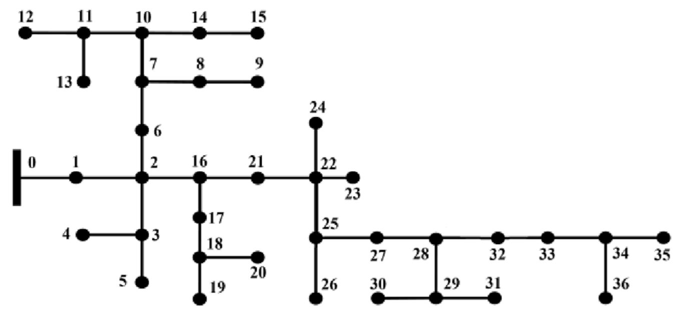

Fig. 3. The considered test system for studying the proposed severe RU/RD management strategy.

in Ref. [41]. It is noteworthy that the optimization formulation is convex and would lead to the optimal point, which would mitigate the severe RU/RD in the MADS. In this regard, the study of the test system is conducted by GAMS using the CPLEX solver.

With regard to the preliminary scheduling of resources in the test system, the highest ramping in net electricity demand of the overall system is about 60 MW/h at hour 4. In this regard, the proposed procedure is applied in the MADS by DSO to motivate the contribution of agents in decreasing the severe RU/RD associated with the system's net electricity demand. Consequently, in the first study, the proposed strategy is applied to limit the RU/RD to 20 MW/h. Accordingly, the MPCC model is firstly implemented to mitigate the severe ramping in hours 1, 8, 9, 10, 13, 15, 16, 17, and 18. Nevertheless, as mentioned, the rebound effect associated with the LFRs' re-scheduling could cause severe ramping at other time intervals. Consequently, the proposed procedure in Fig. 2 is taken into account to manage the severe RU/RD in the test system. Respectively, in the second iteration, the proposed approach results in the optimal re-scheduling of LFRs in order to limit the ramping of the MADS to 20 MW/h. In this regard, the preliminary and the final net-load of the MADS after implementing the proposed approach as well as their respective ramping are shown in Fig. 4. Note that the condition of the system based on the scheduling of local resources before implementing the proposed severe ramping management procedure is called the preliminary net electricity demand/ramping of the system. Regarding the obtained results, the proposed ramping management procedure has efficiently resulted in revising the scheduling of LFRs to limit the ramping to 20 MW/h. The obtained results show that the proposed model for severe ramping alleviation could also flatten the duck curve net electricity demand and stabilize the operation of the network. The bonus paid by the DSO to agents to motivate their contribution in ramping management is shown in Figs. 5–9. Regarding the presented results in Figs. 5 and 6, ESS agents and CDG agents have received incentives to decrease their RD at hours 8–10 that RD violates the considered limitation. Furthermore, as shown in Figs. 7–9, system agents have

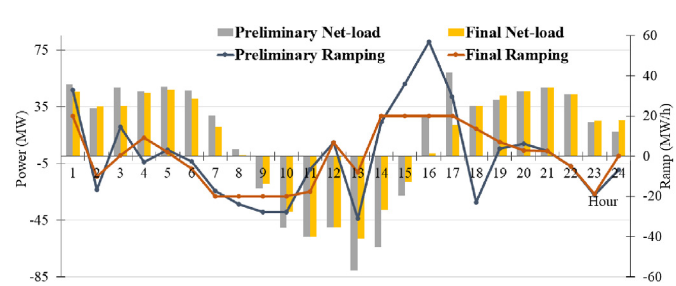

Fig. 4. Preliminary and final net-load/ramping in case of considering ramping limit to be 20 MW/h.

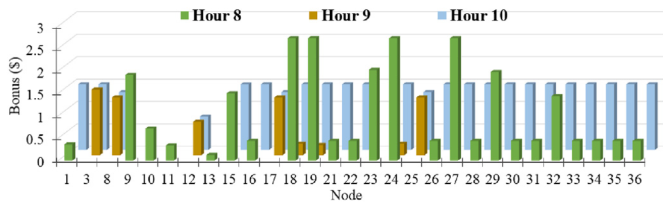

Fig. 5. The received bonus by ESS agents for decreasing their RD.

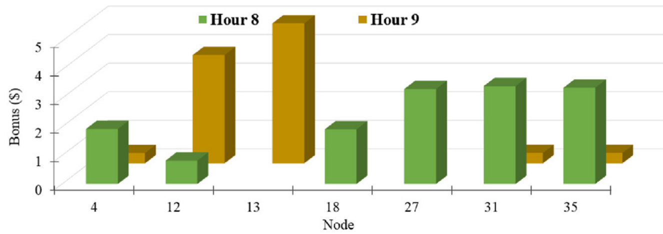

Fig. 6. The received bonus by CDG agents for decreasing their RD.

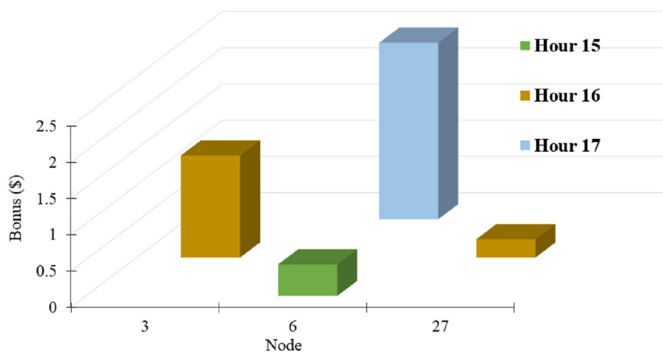

Fig. 7. The received bonus by ESS agents for decreasing their RU.

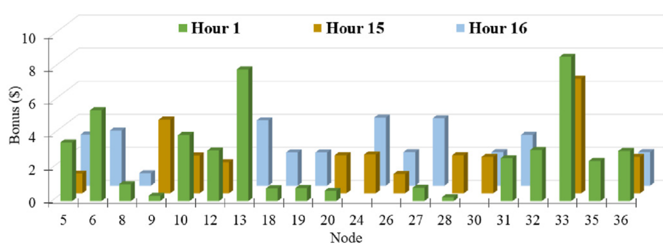

Fig. 8. The received bonus by flexible demand agents for decreasing their RU.

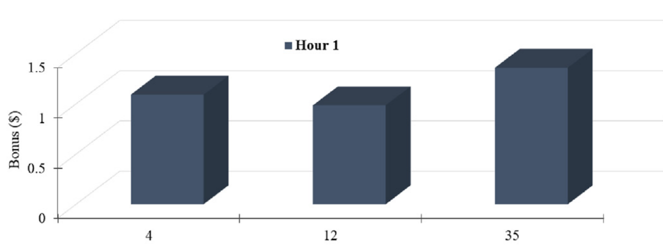

Fig. 9. The received bonus by CDG agents for decreasing their RU.

received bonus in order to contribute to RU management at hours 1, 15–17, that the system confronts with the severe RU. Note that CDG units have higher operational costs compared with VREs. That is why while CDG agents contribute to ramping management; VREs are not curtailed by the DSO in this case study. Furthermore, as an example, the changes in the scheduling of ESS, CDG, and flexible demand agents in nodes 18 and 35 are presented in Figs. 10–12; which shows their contribution in ramping management in case of receiving bonus. It is noteworthy that agents strive to maximize their profits and the received bonuses are based on their contribution in RU/RD management.

In the second study, sensitivity analysis is employed to study the advantages of the proposed approach and its features in the efficient RU/RD management of the system. Accordingly, Fig. 13 shows the power loss in the network in the case of implementing the proposed strategy considering different ramp limits. Accordingly, the power loss is decreased by considering a lower limitation over the RU/RD of the net-load, which shows the importance of

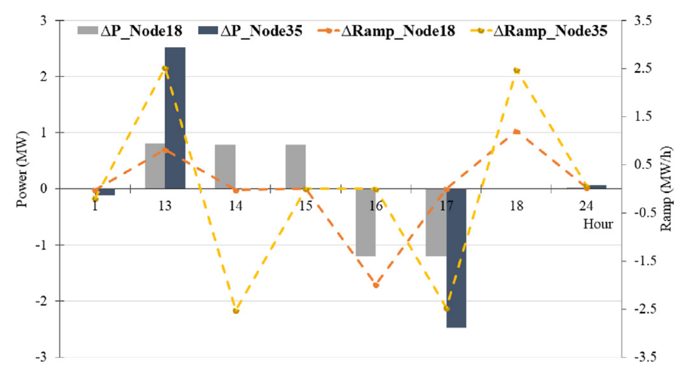

Fig. 10. Changes in power requests by flexible demands in nodes 18 & 35 and their respective effect on the ramping.

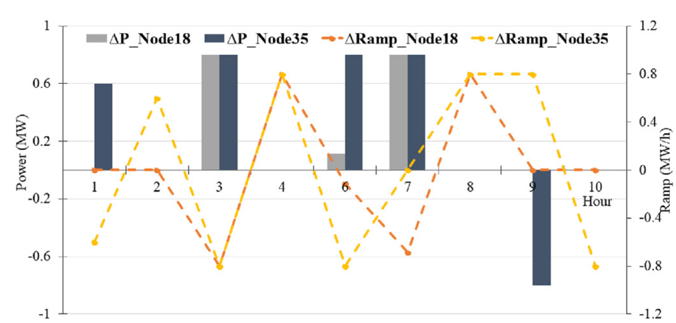

Fig. 11. Changes in power production by CDG agents in nodes 18 & 35 and their respective effects on the ramping.

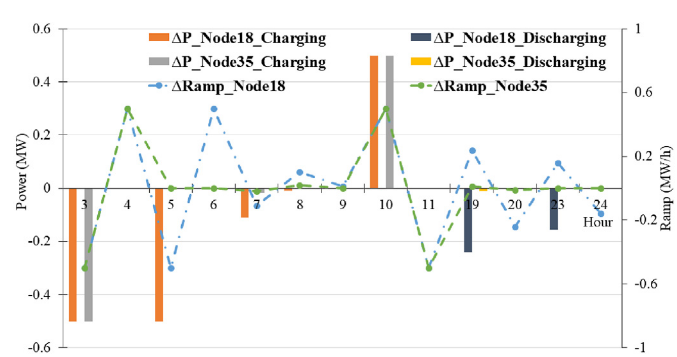

Fig. 12. Changes in power requests by ESS agents in nodes 18 & 35 and their respective effects on the ramping.

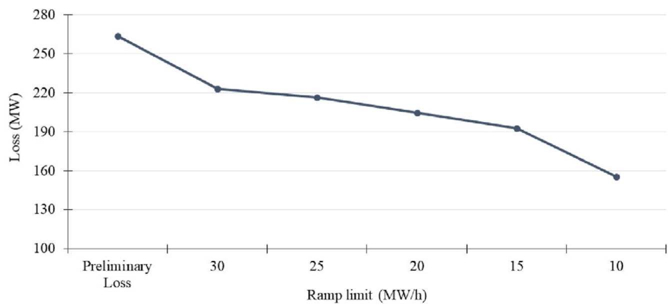

Fig. 13. Power loss in the network after implementing the proposed strategy in case of considering different ramp limits.

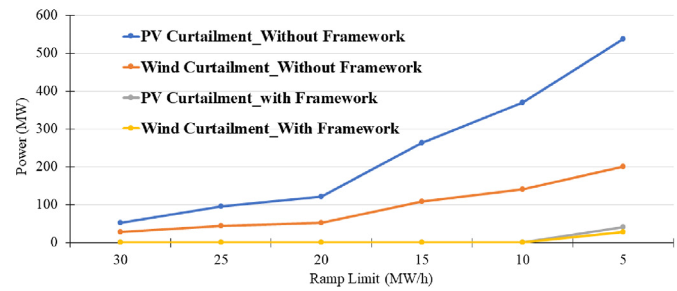

Fig. 16. VREs curtailment with/without implementing the proposed methodology considering different ramp limits.

considering the power loss in the proposed model. In other words, while DSO has to offer bonus to agents in order to revise their preliminary scheduling; the decrease in the power loss could benefit the DSO and partially compensate the ramping management costs. Fig. 14 presents the total bonus received by agents in nodes 17, 18, 24, and 35. Moreover, the total bonus received by all the agents as well as the VREs curtailment while considering different ramp limits are represented in Fig. 15. The obtained results in Figs. 14 and 15 show that, by considering a lower ramp limit, DSO has to offer higher bonus to activate ramp-service in the system. Furthermore, the impact of implementing the proposed strategy on decreasing the VREs curtailment while managing the severe RU/RD in the MADS is investigated in Fig. 16. With regard to the obtained results, the proposed approach would significantly decrease the VREs curtailment which improves the reliability of the system. This condition would finally facilitate higher integration of VREs in the current system, which has advantages for the environment, as well as the operation and investment planning of power systems. Respectively, implementing the proposed strategy, which is based on utilizing the ramp-service supplied by LFRs, would result in effective RU/RD management in MADSs. As a result, the proposed strategy would enhance the flexibility of the system, avoid high price spikes in the system due to flexibility ramping shortages [45], and eventually delay the expansion investments of bulk flexible power units connected to transmission systems.

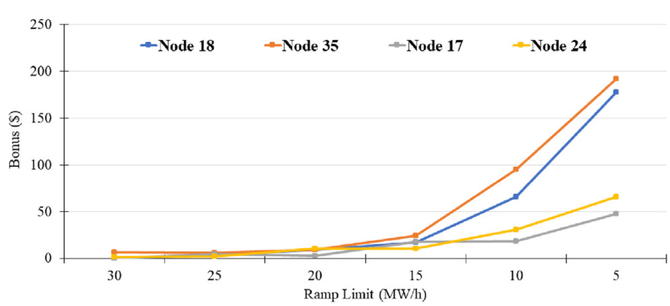

Fig. 14. Total amount of bonus received by agents in nodes 17, 18, 24, and 35 in case of considering different ramp limits.

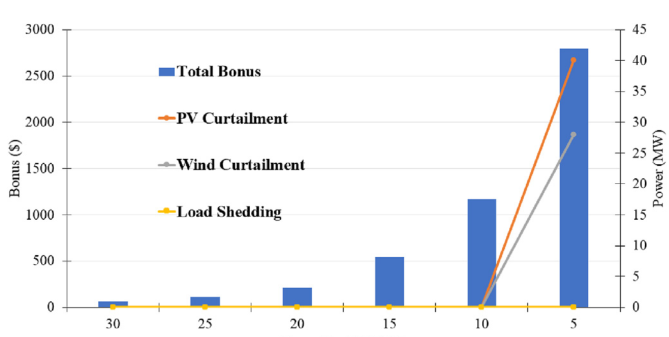

Fig. 15. Total amount of bonus paid by DSO to agents and the VREs curtailment while implementing the proposed methodology considering different ramp limits.

4. Conclusion

In this paper, a new strategy is proposed in order to motivate the contribution of LFRs in RU/RD management of MADSs. Respectively, the Stackelberg game concept is employed to model the proposed RU/RD management strategy, where DSO is conceived as the leading entity and agents act as follower entities operating LFRs. In this respect, DSO offers bonus to agents with the aim of revising their preliminary day-ahead scheduling to decrease the severe RU/RD associated with the MADS's net electricity demand. Accordingly, the proposed approach aims to minimize the VREs curtailment while addressing the RU/RD limitations in the system. Furthermore, to improve the computational efficiency, the strong duality is employed for transforming the bi-level-problem into the MPCC model, which is finally implemented based on a stepwise procedure to mitigate the severe RU/RD in the MADS.

The constructed procedure is applied on the IEEE-37 bus test system, which shows its effectiveness in activating flexibility services to manage the severe RU/RD in MADSs. In this regard, the obtained results in the case study as well as the conducted sensitivity analysis show that optimizing the LFR's scheduling based on the proposed stepwise strategy facilitates mitigating the severe RU/RD in the MADS's net electricity demand while decreasing the VREs curtailment. Moreover, the conducted sensitivity analysis shows the importance of modeling the different cost terms (i.e. power loss) in the proposed RU/RD management strategy. Based on the above discussions, the proposed strategy would enhance the flexibility of the system and decrease the VREs curtailment due to severe RU/RD problems in the system; which would facilitate higher integration of VREs in MADSs. It is noteworthy that, in future works, the proposed strategy could be expanded by modeling the coordination optimization of local electrical and gas grids, which would improve the available flexibility capacity and eventually decrease the cost of conducting the severe RU/RD management strategy in MADSs. In other words, while the focus of the current work is in procuring the flexibility service from LFRs in the electrical network, the interaction of electrical and gas grids and its impacts on managing the RU/RD in the system would be studied in future works.

Credit author statement

Sajjad Fattaheian Dehkordi: Conceptualization, Methodology, Formal analysis, and Writing – original draft. Ali Abbaspour:

Supervision, Writing – review & editing. Mahmud Fotuhi-Firuzabad: Supervision, Writing – review & editing. Matti Lehtonen: Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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