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A Linear-based Model for Multi-Microgrid Energy Sharing- A Western Australia Case Study

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Abstract— This paper proposes a model for energy sharing of interconnected microgrids (MGs), mainly where some MGs are owned by an entity, such as the government, which is the case study in Western Australia (WA). In the proposed model, MGs are able to trade energy among themselves when some of them have surplus generation, and others have lack of generations to meet their demand; however, they are obliged to pay for the use of distribution network, called network charge, and the share of network loss due to this energy transaction. In doing so, the network loss is taken into account and calculated through a power flow. The possibility of energy trading with the main grid is also considered through the wholesale electricity market. Considering the uncertainty of Photovoltaic (PV) generation and load involved, the decision making to inject or import energy to/from the main grid as well as to trade between MGs is obtained through a bi-level linear optimization. In the upper level, the distribution network operator intends to manage the energy exchange between MGs and energy trading with upstream grid, while in the lower level, each MG attempt to minimize its operational cost relating to PV and energy storage system (ESS). Finally, the proposed method is applied to a real project in Western Australia.

***Index Terms*— Bi-level optimization, Energy sharing, Energy storage systems, Linear programming, Microgrid operation, Microgrid, PV generation, Uncertainty.**

NOMENCLATURE

Indices

t	Hourly scheduling intervals $\in \boldsymbol{T}$
n, m	Index of micro-grids $\in \boldsymbol{N}_{MG}$
i, j	Bus Index $\in \boldsymbol{N}_{bus}$

Parameters

$P_{PV}^{Size,n}$	The size of PV panel in n^{th} MG
π_{PV}^{n}	The investment rate of PV panel in n^{th} MG
ξ_{M}^{PV}	A portion of PV panels investment cost for annual maintenance
π_{cyc}^{n}	The cycling cost of ESS in n^{th} MG
$V^{max}(V^{min})$	The maximum (minimum) boundary of bus voltage
$P_{ch}^{max}(P_{dis}^{max})$	The maximum rate of charge (discharge)
$I_{(i,j)}^{max}$	The maximum current capacity of branch between i^{th} and j^{th} buses
P_{load}^{t}	Power demand of the system at t^{th} hour
V_{ss}	Voltage at reference bus (i.e., =1 p.u.)
$\mathcal{T}_{(.)}$	Set of the given discretization of the continuous range $\big(-(.),+(.)\big)$, $(.) = V^{max}, I_{(i,j)}^{max}$
$\mathcal{M}$	A large number (i.e.,10^{10})

Variables

$\mathcal{Z}_{Cost}^{DNO}$	Distribution network operator (DNO) cost
$\mathcal{Z}_{Cost}^{MG}$	MGs total cost
OC_{RES}^{n}	Renewable energy sources operational cost of n^{th} MG
$OC_{ESS}^{n,t}$	ESS operational cost of n^{th} MG at t^{th} hour
π_{ss}^{t}	Energy price at reference bus at t^{th} hour plus network charge
$\pi_{MG}^{t,n}$	Energy exchange price of n^{th} MG at t^{th} hour plus network charge
P_{SS}^{t}	Active power from the substation at t^{th} hour $\in \boldsymbol{P}_{SS}$
$P_{n,m}^{t}$	Active power exchange from n^{th} MG to m^{th} MG at t^{th} hour $\in \boldsymbol{P}_{EEMG}^{t}$
$\boldsymbol{P}_{EEMG}^{t}$	Set of power exchange among MGs at t^{th} hour $\in \boldsymbol{P}_{EEMG}$
$P_{PV}^{n,t}$	The power generation by n^{th} PV at t^{th} hour
$P_{ESS_{ch}}^{n,t}(P_{ESS_{dis}}^{n,t})$	Charge (discharge) power of the n^{th} ESS at t^{th} hour
P_{load}^{t}	Power demand of the system at t^{th} hour
P_{loss}^{t}	Power loss of the system at t^{th} hour
$P_{D,i}^{t}(Q_{D,i}^{t})$	Active (reactive) power consumption of i^{th} bus at t^{th} hour
$P_{G,i}^{t}(Q_{G,i}^{t})$	Active (reactive) power generation of i^{th} bus at t^{th} hour
$B^{n,t}$	Binary variable represents the status of charge (=1) and discharge (=0) of ESS of n^{th} MG at t^{th} hour $\in \boldsymbol{B}^{t}$
$\omega^{max}(\omega^{min})$	The state of charge of ESS of n^{th} MG at t^{th} hour
$\mathbb{N}_{ES}$	The maximum number of charge and discharge
$V_{real,i}^{t}(V_{img,i}^{t})$	Real (imaginary) part of the voltage of i^{th} bus at t^{th} hour
$I_{real,i}^{t}(I_{img,i}^{t})$	Real (imaginary) part of the bus current injection of i^{th} bus at t^{th} hour
$I_{real,(i,j)}^{t}$ $(I_{img,(i,j)}^{t})$	Real (imaginary) part of the branch current between i^{th} and j^{th} buses at t^{th} hour
$g_{i,j}(b_{i,j})$	Conductance and suceptance of branch between i^{th} and j^{th} buses

I. INTRODUCTION

Moving towards more utilization of distributed energy resources (DERs) in smart grids is an inevitable trend that has already started and seems to increase in the near future. In this regards, distribution networks and microgrids (MGs) are the best context of such adoption [1-3]. While internal resources of MGs, such as photovoltaic (PV) generator, micro-turbine (MT) and battery energy storage systems (BESS), potentially offer solutions to benefit both consumers/prosumers by reducing their costs, as well as power system, by alleviating the power losses, more DERs to be used across the distribution network necessities multiple MGs engagement. This means more accurate and reliable energy management needs to be developed to have an optimal operation.

A large body of literature has investigated the optimal management of a single MG in a distribution network. Minchala-Avila *et al.* [4] have developed predictive-based energy management for an islanded MG, in which the states of BESSs and load shedding are optimally determined. Also, a grid-connected model has been proposed in [5], taking advantage of a mixed-integer linear model. The model also considers a set of operational constraints related to unit commitment and exporting/importing energy to the grid. When it comes to grid-connected mode, MGs enables their owners to participate in the electricity market. In this regard, a bi-level scenario-based model has been presented in [6] to operate in the market environment. The first level of the model relates to price modelling, including both day-ahead and real-time market. The second part is to optimize the MG operating points considering the uncertainties involved. Moreover, Hussain *et al.* have introduced a worst-case scenario robust model to investigate the impact of the real-time market on optimal MG management [7]. A similar bi-level robust method is also used in [8] that takes advantage of load shifting to provide more flexible scheduling. The inclusion of thermal demand/generation to MGs can be listed as one of the recent interests of researchers. Hosseinnia and Tousi have presented an optimal MG operation where combined heat and power (CHP) units, boiler and heat storage are taken into account next to the PV units, dispatchable generators and BESS [9]. The model also considers a demand response program for peak shaving purpose to minimize both operational and environmental costs.

Unlike the works reviewed above, recent MGs management schemes revolve around integrated MGs, enabling multi-MGs to share energy between themselves and the main grid with the minimum operational cost [10, 11]. In this respect, Sandgani et al. in [12] have proposed an optimal model to include BESS and renewable energy resources (RESs) in the grid-connected multi-MGs framework. It is worth mentioning that the linear programming approach is the primary advantage of the model. Intending to propose an optimal pricing model in the hour-ahead market, Liu et al. have introduced a nonlinear framework based on the Stackelberg game [13], in which the MG operator acts as a leader and MGs/prosumers are the follows. While the model presented in [12, 13] ignores the network, and consequently, the power loss involved, a linear model for energy cooperation has introduced in [14] that considers the power loss between MGs that are directly connected to each other. However, the power loss of the distribution network has not been taken into account. Few studies have considered distribution network loss in the problem of optimal multi-MGs scheduling [15, 16]. But it is worth mentioning that these models consist of nonlinear terms due to the complexity and nonlinearity of the power flow constraints. Therefore, Particle Swarm Optimization (PSO) and Bender's decomposition algorithms have respectively been used to solve the optimization model proposed in [15] and [16].

Furthermore, Zou et al. in [17] have carried out a survey on the management of interconnected MGs based on three different topologies: radial, daisy-chain and mesh. In the radial structure, which is the case in this paper, no direct energy exchange and information flow exist between MGs, but they are all connected to the main grid, and distributed network operator (DNO) collect the information of MGs [18, 19]. To have a more efficient operation, MGs can be connected through daisy-chain and mesh structures where in the former one each, MG is directly connected to its two adjacent MGs and the main grid [20, 21], while in the latter one, all MGs are directly interconnected [22].

On the one hand, this paper presents a linear-based model for optimal multi-MG energy sharing, in which the exact amount of distribution network loss is taken into account. Thus, comparing to the existing literature, the proposed model would be more comprehensive and mathematically reliable. Moreover, the proposed model is a bi-level optimization, in which the first level is solved in the view of the MG operator in the context of the wholesale electricity market. In more detail, the MG operator takes the load and generation forecasts, including both RESs and diesel generations, of each MG and then initiate the optimization. Based on the solutions of the first level, the optimal scheduling of MGs, such as the BESS state of charges and diesel generator states, is determined through the second level of optimization. Indeed, the second level of optimization is performed from the MG perspective. On the other hand, the case study is a real case in Western Australia, where the network operator imposes the *network charge*, relating to the use of network, on MGs. This cost includes the use of the distribution network as well as the transmission network as a backbone of the system. In this regard, we propose a fair tariff structure for the *network charge*, where one entity or body, such as local government or the owner of retail chains, owns two or some MGs across the network and decides to export from one MG to another.

The remaining part of this paper proceeds as follows: Sections II describes the problem formulation. Mainly, it is divided into two parts, formulating the linear AC power flow and multi-MGs management scheme. Section III represents the simulation results, and finally, Section IV provides some conclusion from this work.

II. Methodology And Framework

The operation of a distribution network with several private micro-grids is modelled through a bi-level optimization problem. At the upper level, the distribution network operator intends to manage the energy exchange between micro-grids and energy trading with the upstream grid. While in the lower level, each micro-grid attempt to minimize its operational cost or maximize the benefit. The detail of each level is provided in de following.

- Upper-Level (DNO)

The DNO coordinates the energy exchange among MGs and energy trading between grid and MGs. The objective function of the system (all sites and the network) is defined as follows.

$$\min_{\Theta_{DSM}}[\mathcal{Z}_{Cost}^{DNO}]$$

$$\mathcal{Z}_{Cost}^{DNO}=\sum_{t\in \boldsymbol{T}}\left(\pi_{ss}^{t}P_{ss}^{t}+\sum_{\substack{m\in \boldsymbol{N}_{MG}\\ m\neq n}}\sum_{n\in \boldsymbol{N}_{MG}}\pi_{MG}^{t,n}\left(P_{n,m}^{t}\right)^{+}\right)+\mathcal{Z}_{Cost}^{MG} \tag{1a}$$

$$s.t.\quad \left(P_{n,m}^{t}\right)^{+}=\max\left(0,P_{n,m}^{t}\right) \tag{1b}$$

$$P_{ss}^{t}=P_{load}^{t}+P_{loss}^{t}+\sum_{n\in \boldsymbol{N}_{MG}}\left(P_{ESS_{ch}}^{n,t}-P_{ESS_{dis}}^{n,t}-P_{PV}^{n,t}\right) \tag{1c}$$

And: *load flow equations* (1d)

To convert the non-linear equation (1b) into linear form, the following technique is used.

$$\left(P_{n,m}^{t}\right)^{+}\geq 0 \qquad \forall n,m,t \tag{2a}$$

$$\left(P_{n,m}^{t}\right)^{+}\geq P_{n,m}^{t} \qquad \forall n,m,t \tag{2b}$$

where, $(P_{m}^{t})^{+}$ is an auxiliary variable to convert $(P_{m}^{t})^{+}=\max(0,P_{n,m}^{t})$ into the linear form in the minimization process.

- The DNO's Decision Variables Vector

$$\Theta_{DNO} = [\boldsymbol{P}_{SS}, \boldsymbol{P}_{EEMG}, (\boldsymbol{P}_{EEMG})^{+}] \quad (3a)$$

$$\boldsymbol{P}_{SS} = (\boldsymbol{P}_{SS}^{t}, \forall t \in \boldsymbol{T}) \quad (3b)$$

$$\boldsymbol{P}_{SS}^{t} = \begin{bmatrix} P_{ss}^{1,t} & P_{ss}^{2,t} & \dots & P_{ss}^{N,t} \end{bmatrix} \quad ,\forall t \in \boldsymbol{T} \quad (3c)$$

$$\boldsymbol{P}_{EEMG} = (\boldsymbol{P}_{EEMG}^{t}, \forall t \in \boldsymbol{T}) \quad (3d)$$

$$\boldsymbol{P}_{EEMG}^{t} = \left(P_{n,m}^{t}, \forall n \in \boldsymbol{N}_{MG}, \forall m \in \boldsymbol{N}_{MG}\right) \quad ,\forall t \quad (3e)$$

$$P_{n,n}^{t} = 0 \quad ,\forall t, n \quad (3f)$$

$$P_{m,n}^{t} = -P_{n,m}^{t} \quad ,\forall t, m, n \quad (3g)$$

$$(\boldsymbol{P}_{EEMG}^{t})^{+} = \left(\left(P_{n,m}^{t}\right)^{+}, \forall n \in \boldsymbol{N}_{MG}, \forall m \in \boldsymbol{N}_{MG}\right) \quad ,\forall t \quad (3h)$$

- Lower Level (MGs or Sites)

The operational cost of MGs includes the battery cycling and degradation cost as well as the maintenance cost of PV panels.

$$\min_{\Theta_{MG}} [\mathcal{Z}_{Cost}^{MG}]$$

$$\mathcal{Z}_{Cost}^{MG} = \sum_{n \in \boldsymbol{N}_{MG}} OC_{RES}^{n} + \sum_{t \in \boldsymbol{T}} \sum_{n \in \boldsymbol{N}_{MG}} OC_{ESS}^{n,t} \quad (4a)$$

$$OC_{RES}^{n} = \left(\xi_{M}^{PV} \pi_{PV}^{n} P_{PV}^{Size,n}\right)/365 \quad ,\forall n \quad (4b)$$

$$OC_{ESS}^{n,t} = \pi_{cyc}^{n} |B^{n,t} - B^{n,t-1}| \quad ,\forall t, n \quad (4c)$$

$$0 \leq P_{ESS_{ch}}^{n,t} \leq P_{ch}^{max} B^{t} \quad ,\forall t, n \quad (4d)$$

$$0 \leq P_{ESS_{dis}}^{n,t} \leq P_{dis}^{max} (1 - B^{n,t}) \quad ,\forall t, n \quad (4e)$$

$$\omega^{n,t} = \omega^{n,t-1} + \rho_{ch} P_{ESS_{ch}}^{n,t} - P_{ESS_{dis}}^{n,t} / \rho_{dis} \quad ,\forall t, n \quad (4f)$$

$$\omega^{min} \leq \omega^{n,t} \leq \omega^{max} \quad ,\forall t, n \quad (4g)$$

$$\omega^{n,T} = \omega^{n,0} \quad ,\forall t, n \quad (4h)$$

$$\sum_{t=2}^{T} |B^{n,t} - B^{n,t-1}| \leq \mathrm{N}_{ES} \quad ,\forall n \quad (4i)$$

To convert the non-linear equation into linear form, the following technique is used.

$$\sum_{t=2}^{T} BC^{n,t} \leq \mathrm{N}_{ES} \quad (5a)$$

$$BC^{n,t} \geq B^{n,t} - B^{n,t-1} \quad ,\forall n, t = 2,3, \dots, T \quad (5b)$$

$$BC^{n,t} \geq B^{n,t-1} - B^{n,t} \quad ,\forall n, t = 2,3, \dots, T \quad (5c)$$

where, $BC^{n,t}$ is an auxiliary binary variable to convert $BC^{n,t} = |B^{n,t} - B^{n,t-1}|$ into the linear form in the minimization process.

- The MG's Decision Variables Vector

The charge and discharge of the battery and the status of charge and discharge are included in the MG's decision variables.

$$\Theta_{MG} = \left[\boldsymbol{P}_{ESS_{ch}}, \boldsymbol{P}_{ESS_{dis}}, \boldsymbol{B}, \boldsymbol{BC}\right] \quad (6a)$$

$$\boldsymbol{P}_{ESS_{ch}} = \left(\boldsymbol{P}_{ESS_{ch}}^{t}, \forall t \in \boldsymbol{T}\right) \quad (6b)$$

$$\boldsymbol{P}_{ESS_{ch}}^{t} = \left[P_{ESS_{ch}}^{1,t}, P_{ESS_{ch}}^{2,t}, \dots, P_{ESS_{ch}}^{N,t}\right] \quad (6c)$$

$$\boldsymbol{P}_{ESS_{dis}} = \left(\boldsymbol{P}_{ESS_{dis}}^{t}, \forall t \in \boldsymbol{T}\right) \quad (6d)$$

$$\boldsymbol{P}_{ESS_{dis}}^{t} = \left[P_{ESS_{dis}}^{1,t}, P_{ESS_{dis}}^{2,t}, \dots, P_{ESS_{dis}}^{N,t}\right] \quad (6e)$$

$$\boldsymbol{B} = (\boldsymbol{B}^{t}, \forall t \in \boldsymbol{T}) \quad (6f)$$

$$\boldsymbol{B}^{t} = [B^{1,t}, B^{2,t}, \dots, B^{N,t}] \quad (6g)$$

$$\boldsymbol{BC} = (\boldsymbol{BC}^{t}, \forall t \in \boldsymbol{T}) \quad (6h)$$

$$\boldsymbol{BC}^{t} = [BC^{1,t}, BC^{2,t}, \dots, BC^{N,t}] \quad (6i)$$

- Network modeling and load flow equations

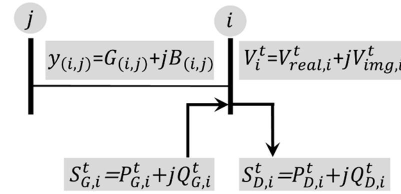

Fig.1: A simple node for KCL presentation

The AC power flow equations are considered to model the limitation and constraints of the networks.

The KCL equations regarding Fig.1 are as follow:

$$2P_{D,i}^{t} - P_{G,i}^{t} \approx \frac{P_{D,i}^{t}}{V_{ss}} V_{real,i}^{t} - \frac{Q_{D,i}^{t}}{V_{ss}} V_{img,i}^{t} - V_{ss} I_{real,i}^{t} \quad ,\forall i, t \quad (7a)$$

$$2Q_{D,i}^{t} - Q_{G,i}^{t} \approx \frac{Q_{D,i}^{t}}{V_{ss}} V_{real,i}^{t} - \frac{P_{D,i}^{t}}{V_{ss}} V_{img,i}^{t} + V_{ss} I_{img,i}^{t} \quad ,\forall i, t \quad (7b)$$

The linear approximation of the above KCL equations can be obtained based on the second order of Taylor expansion.

Separating the real and imaginary parts of the KVL equations.

$$I_{real,i}^{t} = \sum_{j \in \boldsymbol{N}_{bus}} G_{i,j} V_{real,i}^{t} - \sum_{j \in \boldsymbol{N}_{bus}} B_{i,j} V_{img,i}^{t} \quad (8d)$$

$$I_{img,i}^{t} = \sum_{j \in \boldsymbol{N}_{bus}} G_{i,j} V_{img,i}^{t} + \sum_{j \in \boldsymbol{N}_{bus}} B_{i,j} V_{real,i}^{t} \quad (8e)$$

The voltage and current constraints:

$$(V^{min})^2 \leq \left(V_{real,j}^{t}\right)^2 + \left(V_{img,j}^{t}\right)^2 \leq (V^{max})^2 \quad (9a)$$

$$\left(I_{real,(i,j)}^{t}\right)^2 + \left(I_{img,(i,j)}^{t}\right)^2 \leq \left(I_{(i,j)}^{max}\right)^2 \quad (9b)$$

$$I_{real,(i,j)}^{t} = g_{i,j}\left(V_{real,i}^{t} - V_{real,j}^{t}\right) - b_{i,j}\left(V_{img,i}^{t} - V_{img,j}^{t}\right) \quad (9c)$$

$$I_{img,(i,j)}^{t} = g_{i,j}\left(V_{img,i}^{t} - V_{img,j}^{t}\right) + b_{i,j}\left(V_{real,i}^{t} - V_{real,j}^{t}\right) \quad (9d)$$

To this end, the hexagon linear approximation is used by the technique below that is introduced in [23].

$$\left|V_{img,i}^{t}\right| \leq \frac{-\zeta V_{real,i}^{t} + (V^{max})^2}{\sqrt{(V^{max})^2 - \zeta^2}} \quad ,\forall t, i, \forall \zeta \in \boldsymbol{\mathcal{T}}_{V^{max}} \quad (10a)$$

$$V^{min} \leq V_{real,i}^{t} \quad ,\forall i, t \quad (10b)$$

$$\left|I_{img,(i,j)}^{t}\right| \leq \frac{-\zeta I_{real,(i,j)}^{t} + \left(I_{(i,j)}^{max}\right)^2}{\sqrt{\left(I_{(i,j)}^{max}\right)^2 - \zeta^2}} \quad ,\forall t, (i,j), \forall \zeta \in \boldsymbol{\mathcal{T}}_{I_{(i,j)}^{max}} \quad (10c)$$

The generation and consumption of each bus:

$$P_{i}^{D} = P_{load}^{i,t} \quad \forall i \in \boldsymbol{N}_{MG} \quad (11a)$$

$$Q_{D,i}^{t} = P_{D,i}^{t} tan(\varphi_i) \quad \forall i \in \boldsymbol{N}_{bus} \quad (11b)$$

$$P_{G,i}^{t} = P_{PV}^{i,t} + P_{ESS_{dis}}^{i,t} - P_{ESS_{ch}}^{i,t} + \sum_{\substack{m \in \boldsymbol{N}_{MG} \\ m \neq i}} \left(\left(P_{i,m}^{t}\right)^{-} - \left(P_{i,m}^{t}\right)^{+}\right) \quad \forall i \in \boldsymbol{N}_{MG} \quad (11c)$$

$$Q_{G,i}^{t} = P_{G,i}^{t} tan(\varphi_i) \quad \forall i \in \boldsymbol{N}_{bus} \quad (11d)$$

$$\left(P_{i,m}^{t}\right)^{-} = min\left(0, P_{i,m}^{t}\right) \quad \forall i \in \boldsymbol{N}_{bus} \quad (11e)$$

The Eq (10e) is nonlinear, and the following technique is implemented to convert it into the linear form.

$$\left(P_{i,m}^{t}\right)^{-} \leq 0 \quad (12a)$$

$$\left(P_{i,m}^{t}\right)^{-} \leq P_{i,m}^{t} \quad (12b)$$

$$\left(P_{i,m}^{t}\right)^{-} \geq P_{i,m}^{t} + \left(1 - N_{i,m}^{t}\right)\mathcal{M} \quad (12c)$$

$$\left(P_{i,m}^{t}\right)^{-} \geq -N_{i}^{t}\mathcal{M} \quad (12d)$$

In the proposed model, the power loss equation is linear and defined as follows:

$$P_{loss}^{t} = V_{ss} I_{ss}^{real} + \sum_{n\in \boldsymbol{N}_{MG}} \left(P_{PV}^{n,t} + P_{ESS_{dis}}^{n,t} - P_{ESS_{ch}}^{n,t}\right) - \sum_{j\in \boldsymbol{N}_{bus}} P_{load}^{j,t} \quad ,\forall t \tag{13a}$$

- Uncertainty Modelling

The upper level of the problem includes uncertainty parameters such as energy price ($\pi_{ss}^{t}, \pi_{MG}^{t,n}$), load ($P_{load}^{t}$) and PV power generation ($P_{PV}^{n,t}$). In this regard, a robust optimization approach is implemented to reach robust solutions.

For notation convenience, first, the general form of the upper level part of the problem is presented as follows:

$$\underset{X}{\text{Min}}\; c_i^T X + L \tag{14a}$$

$$s.t. \quad a_i^T X \le b_i \quad \forall a_i \in \Omega_a, \quad \forall a_i \in \Omega_a \tag{14b}$$

$$d_i^T X = e_i \quad \forall d_i \in \Omega_d, \quad \forall e_i \in \Omega_e \tag{14c}$$

where, c_i includes energy prices; X is the decision variables vector; L is $\mathcal{Z}_{Cost}^{MG}$; In addition, (14b) includes (2a), (2b), (10a), (10b), (10c), (12a), (12b), (12c), and (12d), Also (14c) includes (1c), (7a), (7b), (8d), (8e), (9c), (9d), (11a), (11b), (11c), (11d), and (13a).

The uncertainty sources are energy price (c_i^T), loads (e_i^T) and RES power generation (e_i^T). To ensure solution robustness against loads and RES power generation uncertainties, the selected vertex scenarios (SVS) is considered. SVS is the key to guaranteeing the robustness of problem solutions, which is defined as $\max e_i^T = \max(\text{demand}) - \min(\text{RES generation})$. In fact, the scenario represents the maximum net residual load demand (as the worst-case scenario for load and RES uncertainty). It has been proved in [24] that the robustness of dispatch-able units output solutions can be guaranteed by SVS. Therefore, the uncertainty e_i^T can be eliminated as the worst-case scenario is achieved at the lower end of the interval $u_i = \max e_i^T \;\; \forall e_i^T \in \Omega_e$, and accordingly the constraint (14a) would be as $d_i^T X = u_i \;\; \forall d_i \in \Omega_d, \; \forall u_i \in \Omega_u$.

In addition, the problem can be reformulated as follows to get rid of equality constraints.

$$\min_{X} c_i^T X + L \tag{15a}$$

$$s.t. \quad a_i^T X \le b_i \quad \forall a_i \in \Omega_a, \quad \forall a_i \in \Omega_a \tag{15b}$$

$$d_i^T X \le u_i \quad \forall d_i \in \Omega_d, \quad \forall u_i \in \Omega_u \tag{15c}$$

$$-d_i^T X \le -u_i \quad \forall d_i \in \Omega_d, \quad \forall u_i \in \Omega_u \tag{15d}$$

Then all inequality constraints are combined as follows:

$$\min_{X} c_i^T X + L \tag{16a}$$

$$s.t. \quad f_i^T X \le k_i \quad \forall f_i \in \Omega_f, \quad \forall k_i \in \Omega_k \tag{16b}$$

where, $\Omega_f = \Omega_a \cup \Omega_d$, and $\Omega_k = \Omega_b \cup \Omega_e$.

In this case, the only uncertainty source is energy price (c_i^T), which this uncertainty in the objective function becomes linear by adding a new variable ξ:

$$\min_{X,\xi} \xi \tag{17a}$$

$$s.t. \quad f_i^T X \le k_i \quad \forall f_i \in \Omega_a, \quad \forall k_i \in \Omega_b \tag{17b}$$

$$c_i^T X + L \le \xi \quad \forall c_i \in \Omega_c \tag{17c}$$

Two inequality constraints can be combined and reformulate the problem as follows:

$$\min_{X,\xi} \xi \tag{18a}$$

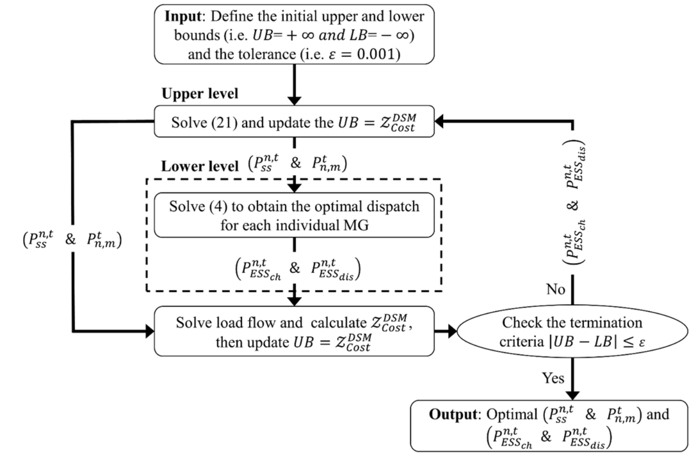

Fig.2: Bi-level optimization steps.

$$s.t. \quad g_i^T X \le h \quad \forall g_i \in \Omega_g \tag{18b}$$

where, $\Omega_g = \Omega_f \cup \Omega_c$, and $h = \{k\} \cup \{\xi\}$.

In this formulation, the only uncertain parameters are g_i. Then it can be modelled as ellipsoidal uncertainty.

$\Omega_g = \{\overline{g_i} + w_i y | \, \|y\|_2 \le 1\}, \qquad i = 1, \dots, m,$

where, $\overline{g_i} \in \mathbb{R}^n$ is the fixed input, and $w_i \in \mathbb{R}^{n\times n}$ is known parameter.

Once again, the problem can be reformulated as follows:

$$\min_{X,\xi} \xi \tag{19a}$$

$$s.t. \quad \begin{bmatrix} \max\limits_{g_i} g_i^T X \\ g_i \in \Omega_g \end{bmatrix} \le h \;\; , \;\; i = 1, \dots, m \tag{19b}$$

The explicit solution can be found for the interior maximization problem as follows:

$$\max_{g_i} g_i^T X = \max_{y} \overline{g_i} X + w_i y X = \overline{g_i} X + \max_{y}\{w_i y X | \, \|y\|_2 \le 1\} = \overline{g_i} X + \|w_i X\|_2 \tag{20a}$$

Therefore, the robust linear problem turns to the deterministic second order cone problem.

$$\min_{X,\xi} \xi \tag{21a}$$

$$s.t. \quad \overline{g_i} X + \|w_i X\|_2 \le h \;\; , \;\; i = 1, \dots, m \tag{21b}$$

- Iterative Approach for Optimization

As previously mentioned, the proposed model is a bi-level optimization problem which can be presented as in Fig. 2. Indeed, the bi-level optimization follows the following steps.

- Step 1: Initializing the upper and lower bounds (i.e. UB=$+\infty$ and LB=$-\infty$) and the tolerance (i.e. $\varepsilon = 0.001$).
- Step 2: Solving the upper-level problem to find a feasible solution $\left[\Theta_{DNO}{}^{i}\right]$ at i^{th} iteration.

$$\min_{X,\xi} \xi \tag{22a}$$

$$s.t. \quad \overline{g_i} X + \|w_i X\|_2 \le h \;\; , \;\; i = 1, \dots, m \tag{22b}$$

Afterwards, update the lower bound with LB=$(\mathcal{Z}_{Cost}^{DNO})^{i}$.

- Step 3: Considering $\left[\Theta_{DNO}{}^{i}\right]$ as the input of the lower-level problem, and solve the lower-level problem to obtain $\left[\Theta_{MG}{}^{i}\right]$,

$$\min_{\Theta_{MG}} [\mathcal{Z}_{Cost}^{MG}]$$

$$s.t. \text{ (4d), (4e), (4f), (4g), (4h), (4i), (5a), (5b), (5c)} \tag{22c}$$

Then update the upper bound UB=$(\mathcal{Z}_{Cost}^{MG})^{i}$.

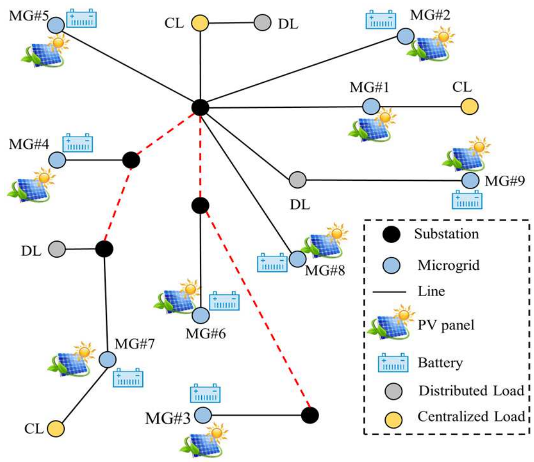

Fig.3: Case study of the local government -Western Australia

- Step 4: Check the termination criterion ($UB - LB \leq \varepsilon$).

III. Simulation Results

A. Case Study

This study is a part of an initiative project funded to explore opportunities for optimizing renewable energy use in distributed local government facilities in Western Australia. The case study comprises nine MGs with PV and battery installed, three sites or nodes known as centralized loads, and three nodes known as distributed loads, each of which is modelled in the middle of the feeder. All nodes are geographically distributed in different suburbs, as depicted in Fig.3. PV sizes for MG1 to MG9 are considered to be 100kW, 150kW, 96 kW, 255 kW, 13 kW, 4.5 kW, 94 kW, 40 kW and 12 kW. Similarly, battery sizes for MG1 to MG9 are 0 kWh, 57kWh, 49 kWh, 58 kWh, 0.5 kWh, 1.5 kWh, 34 kWh, 12 kWh and 9 kWh. Moreover, PV generation and the load profile associated with MGs have been clustered season-wise across a year as other inputs to this study.

B. Proposed Energy Sharing Mechanism

In this section, the proposed energy sharing scheme is applied to the case study as a collaborative scenario. Table I demonstrates the results. To have a better understanding of the benefit gained, the results are also compared to those of non-collaborative scenario where MGs interact only with grids, meaning MGs can sell their surplus to the grid and buy their energy shortage off the grid based on the wholesale market. As can be seen (Table I), the total cost of MGs has dropped to 341,355.3 $/year from 36,5084 $/year (i.e. 23,728.7 $/year benefit is gained). Also, the costs of all MGs have reduced compared to the non-collaborative scenario due to energy sharing between MGs and importing less energy from the grid. This improvement, in such a small case study, reveals that there is an economic opportunity when all local governments in WA follow the proposed scheme. Moreover, future grants to deploy more renewable energies in local government facilities would bring more benefits.

To demonstrate the details of energy sharing in this study, MG2 and MG7 have been selected as examples. The corresponding load and PV profiles and their energy transactions with grid and other MGs as well as battery SOC have been illustrated in Fig. 4 and Fig 5. As it can be seen, these two MGs

Table I. Comparison of the proposed energy sharing mechanism with the traditional scheme

Case	Collaborative	Non-Collaborative
MG1 Cost ($/year)	182,062	187,172
MG2 Cost ($/year)	49,665.55	55,198.95
MG3 Cost ($/year)	15,355.55	15,746.1
MG4 Cost ($/year)	21,334.25	24,455
MG5 Cost ($/year)	31,240.35	37,222.7
MG6 Cost ($/year)	20,385.25	21,983.95
MG7 Cost ($/year)	15,103.7	16,260.75
MG8 Cost ($/year)	2,620.7	3,102.5
MG9 Cost ($/year)	3,587.95	3,942
Total MGs Cost ($/year)	341,355.3	365,084
Energy loss (kWh/year)	1,321,406	1,321,556
Energy from upstream grid (kWh/year)	21,203,887	21,224,206

operate in a different situation. For example, the PV generation of MG2 is less than its load, while this is not the case for MG7. Also, the load of MG2 in holidays and weekends (H&W cluster) significantly drops, while for MG7, it is similar to other clusters. Such varieties in MGs' characteristics result in different energy management solutions for every MG. From Fig. 4, MG2 in seasonal clusters not only uses its own PV generation (yellow dots) to meet the load but also imports energy from other MGs (blue dots with positive values). There is still some shortage which is solved by importing energy from the grid (red dots). However, the situation for the H&W cluster is different, and it can meet its demand and export its surplus energy to other MGs who are in need (please note that the blue dots for this cluster have negative values). It is worth noting that when an MG exports its surplus energy to other MGs, the cost imposed to receiving MGs is calculated based on the levelized cost of energy (LCOE), and the network charge involved has a fixed daily component for each MG (2.99 $/day) plus a variable one depending on the amount of energy exchanged (12 cent/kWh and 27 cent/kWh for off-peak and on-peak periods, respectively), which all have been considered in this study. Furthermore, from Fig. 5, it is clear that MG7 relies on its own PV generation during daylight, and there is no need to import from the grid (red dots with zero value). It is also interesting to see that during autumn and winter, when PV generation drops, MG7 is not able to contribute to energy sharing with other MGs.

IV. Conclusion

In this study, a linear framework for energy trading has been proposed, enabling multiple MGs to share energy among themselves and/or the main grid. Next to the PV and load uncertainties, the network loss has been accurately modelled. The model specifically helps an entity owning multiple MGs to optimally trade and operate energy among its MGs as well as the main grid when needed. Indeed, the proposed model addresses those questions regarding when to trade with the network (both import and export energy) considering the market price and when and how much to trade with other MGs regarding the charge due to network usage, network charge, and loss. To operate PV and ESS to get the optimal solution for the mentioned questions, a linear bi-level optimization has been used and tested on a Western Australia's (WA) trial network, where a few

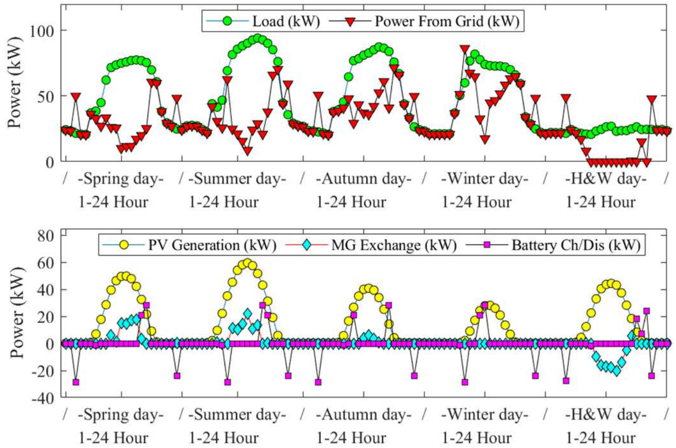

Fig.4: MG2- The obtained operational results of energy exchange with grid and other MGs based on the proposed mechanism against MG2's load profile and PV generations.

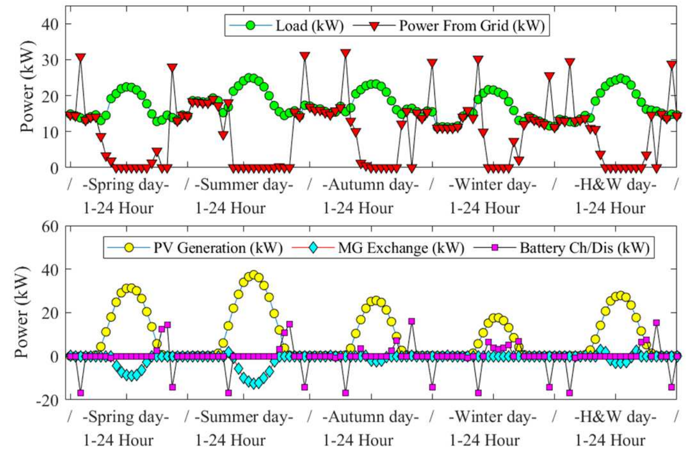

Fig.5: MG7- The obtained operational results of energy exchange with grid and other MGs based on the proposed mechanism against MG7's load profile and PV generations.

geographically distributed MGs are owned by a local government. The obtained results reveal that the operational cost based on the collaborative scenario (where MGs exchange energy among themselves and pay for the network charge) is lower than the case each MG trades with the grid. The results encourage WA's large entities, such as local governments, to act as a retailer and to consider exchanging energy among their MGs within their energy management model.

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