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Smart Energy Dispatch for Networked Microgrids Systems Based on Distributed Control Within a Hierarchy Optimization

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Abstract: Cooperative microgrids considered the next generation of smart energy trading technology. A promising solution is proposed in this paper, for smart energy management of cooperative multi microgrids (MMGs) systems based on dual level distributed strategy, achieved by two layers model predictive control (MPC) for optimal operation and energy scheduling of the DERs, and energy trading among multi-microgrids system, with efficient economic cost reduction. We employed a distributed system operator (DSO) as a supervisory layer for energy trading and dynamic power balance ensuring. Along with the local controller as a lower layer for tracking a reference trajectory from the upper layer, we developed an online algorithm with a hierarchical structure to solve the energy dispatching problem within dual-level optimization, offering an environmental-friendly control solution, due to reduction of fuel consumption. Finally, simulation results are presented to witness the advantages of our distributed algorithm approach in comparison to a noncooperative strategy.

Keywords: Microgrids, MPC, Smart grid, energy management, Dual-level optimization.

1 INTRODUCTION

In recent years, new technologies and policies were set up to fight climate change and improve the use of renewable energy in the world. Paris deal was the world's first official climate agreement to propose eco-friendly solutions by integrating a renewable energy RES and reducing carbon emission. Several control techniques have been applied to improve the energy management of microgrids systems while reducing the dependency on the conventional energy source see (Minchala-Avila et al., 2015; Venayagamoorthy et al., 2016).

The main objective of the smart energy management system is to provide efficient distribution of controllable active power within an optimal energy dispatch. In (Papavasiliou et al. 2018)proposed a multi-stage stochastic for the storage system. Another work made by (Ju et al. 2018) offers a two-layer EMS considering degradation costs of batteries. Recently, energy companies and R&D power institutes focus on the use of Model Predictive Control MPC in energy management and power systems modeling. In (Parisio et al. 2017), the authors proposed a robust MPC for residential microgrids.

In another work, see (Zhai et al., 2018), authors employed the robust MPC for isolated microgrids optimization. Other enhanced approaches based on multi-layer MPC has introduced for islanded microgrids, see (Hajar et al., 2016; Legry et al., 2018), However, the previously mentioned methods based on centralized MPC may to the high computational burden time when processing a large amount of data from the central controller, also the high costs of centralized installations due to geographic details in real-world applications. As an alternative, distributed MPC DMPC methods show more flexibility, where the information can be exchanged with efficiency between subsystems, see (Mehrizi-Sani 2017) and our previous work (Brahmia et al., 2019), in which we employed DMPC for multi-microgrids with a single layer optimization. In (Rezaei and kalantar 2015), the authors proposed novel hierarchical energy management with the distribution system operator (DSO) for multi-microgrids based on dynamic frequency control

Enthused by the above discussion, this paper presents a novel hierarchical optimization based on DMPC for optimal energy management of resilient multi microgrids operated in off-grid mode. To recap, the main contributions of this paper can be highlighted as follows

- We proposed an innovative dual-level optimization within a hierarchical distributed strategy for cooperative multi-microgrids systems based on economic energy dispatch.
- A promising solution for smart cities, and the next generation of intelligent microgrids, with efficient renewable energy utilization for cooperative MMGs.

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- We developed a coordinated energy management strategy supervised by a distribution system operator DSO to guarantee the power demand-supply balance.
- We propose a smart energy management framework to optimize the MMGs network in an economic-environmental friendly framework.

This paper focuses on the mentioned points above and is organized as follows. In section 2, the description of components model and modeling. In section 3 introduces of dual-level distributed MPC. In section 4, the validation results. In section 5, we conclude the paper with current achievement and future works

2 SYSTEM DESCRIPTION AND MODELLING

2.1 System Overview

In this paper, we consider a smart cooperative microgrids MMGs illustrated in Fig.1. Each MG contain a renewable energy RESs with Wind Turbines (WT) and photovoltaic (PV) solar panels plus energy storage system (ESSs), a local load from a smart building as load demand, for example, we have a clinic, office building, and residential component, The distributed generators units (ESS, WT, PV, DG) are connected to a local controller (LC), All MMGs are connected to distributed system operator DSO which receives information data from MG and decides the surplus energy distribution among MMGs plant, The DSO consider as higher level, for the efficient energy dispatching while minimizing the operating cost of the DERs.

Fig. 1. Schematic for smart cooperative MMGs

2.2 System Modelling and Components

2.2.1 Energy storage system

To guarantees the energy supply and smooth intermittent of renewable energy, it is crucial to employ the storage system devices. See (Parisio, Rikos, & Glielmo, 2014). The batteries dynamic model is introduced as follows

$$E_i^b(k+1) = E_i^b(k) + \eta_i P_i^b(k)\Delta t - \varepsilon_{bess}\Delta t \qquad (1)$$

Where

$$\eta_i = \begin{cases} \eta^{charg}, & \text{if } P_i^b(k) > 0 \quad \text{(charging mode)} \\ 1/\eta^{disch}, & otherwise \quad \text{(discharge mode)} \end{cases}$$

the constraint (2) for the energy stored capacity to prevent storage system degradation.

$$\underline{E}_i^{dch} \le E_i(k) \le \overline{E}_i^{chr} \qquad (2)$$

Where $\underline{E}_i^{dch}, \overline{E}_i^{chr}$ denote minimum discharge and maximum charging. The operation and maintenance O&M cost of the battery in every time interval can be expressed as follows

$$C_i^b(k) = [2z_i^b(k) - P_i^b(k)]OM_b\Delta t \qquad (3)$$

Wheig.re $z_i^b = \delta^b(k)P_i^b(k)$ a positive value to improve the efficiency and flexibility of battery operation within the range of power charging/discharging limits $[\underline{P}_i^b, \overline{P}_i^b]$.

2.2.2 Load Demand Model

In this paper, we consider two types of loads:

Critical load: denoted by P_i^{CL}, refer to the load that must always be satisfied within the demand-supply balance for a specific prediction horizon; for instance, emergency lighting, hospital ventilator machines, in this paper is defined as.

Controllable load: denoted by P_i^{SL}, consider as flexible load and can be controlled and scheduled for a later time, for example, hybrid electric vehicle charging that can be planned for a later time if the vehicle would not be in use soon. See (Nadar, 2013), the total load denoted by P_i^L for the total of customer demand for each microgrid in the MMGs plant subject to the following dynamic model

$$P_i^L(k) = P_i^{CL}(k) + P_i^{SL}(k) \qquad (4)$$

$$\underline{P}_i^L \le P_i^L(k) \le \overline{P}_i^L \qquad (5)$$

$$0 \le P_i^{SL}(k) \le \overline{P}_i^{SL} \qquad (6)$$

Where *i=1…M,* is the number of microgrids $\underline{P}_i^L$ and $\overline{P}_i^L$ corresponding respectively to a minimum and maximum active controllable power. The curtailment penalty cost on the controllable load for the objective to consider customer comfort.

$$C_{cur}(P_i^{SL}) = \sum_{i=1}^{M_L} \alpha_{i,cur}(k)\beta_{i,cur}(k)P_i^{SL}(k)\Delta t \qquad (7)$$

Where β_i a positive value limited in the range $[\overline{\beta}_i, \underline{\beta}_i]$

$\alpha_{i.cur}$ is the penalty factor (Zhai et al. (2017)).

2.2.3 Diesel generator model

The diesel generators can be scheduled over a specific horizon see (Sachs & Sawodny, 2016), constraints on DGs operation are introduced as follows

$$\delta_{i,k}^{DG}\underline{P}_i^{DG}(k)\le P_i^{DG}(k)\le \delta_{i,k}^{DG}\overline{P}_i^{DG}(k) \quad (8)$$

Where $\delta_{i,k}^{DG}=\begin{cases}1, & P_i^{DG}(k)>0\\ 0, & P_i^{DG}(k)=0\end{cases}$ switch *(On\Off)*

$$\delta_i^{DG}(k)-\delta_i^{DG}(k-1)\le \delta_i^{DG}(\tau_1) \quad (9)$$

$$\delta_i^{DG}(k-1)-\delta_i^{DG}(k)\le 1-\delta_i^{DG}(\tau_2) \quad (10)$$

The power flow capacity in (8) defines the limit of generator units. The status on/off with $i=1,...,M_{DG}$ the number of diesel generators, the equation (9), and (10) used for on the minimum up/downtime operation constraint. τ_1,τ_2 are auxiliary variables, see (Parisio, Rikos, Tzamalis, et al., 2014).

The fuel cost can be modeled by a quadratic polynomial function (11), with *(a,b)* and *(c)* are the coefficients of DGs and $P_i^{DG}(k)$ is the output power at time *k*.

$$C_{DG}(P_i^{DG})=(a_i(P_i^{DG})^2(k)+b_iP_i^{DG}(k)+c_i)\Delta t \quad (11)$$

2.2.4 Renewable energy supply

There are several types of renewable energy generation such that the PV-solar panels and wind turbines. However, their power output depends on meteorological uncertainties; in this paper, the total power generated from the RES denoted as $P_{i,k}^{RES}$. The constraints on the renewable energy expressed as

$$\underline{P}_i^{RES}\le P_{i,k}^{RES}\le \overline{P}_i^{RES},\forall\ i\in M \quad (12)$$

Where $\underline{P}_i^{RES}$ and $\overline{P}_i^{RES}$ represent the minimum and maximum of renewable power generation.

2.2.5 Power balance

The supply-demand balance for the cooperative multi microgrids plant operated in autonomous mode must be achieved for each microgrid. The dynamic power balance for the coordinated multi-microgrids system can be formulated as follows

$$\begin{aligned}P_i^m(k)=P_i^{DG}(k)+P_{surp}(k)+E_i^{chr}(k)\\ -E_i^{dch}(k)-P_i^{SL}(k)\end{aligned} \quad (13)$$

Where

$$P_i^m=P_i^L-P_i^{RES}$$

$$P_{surp}=\sum_{j\ne i}^{M}a_{ij}(P_j^{RES}(k)-P_j^L(k))$$

$$P_i^{surp}\ge 0 \quad (14)$$

The condition (14) on the power surplus prioritize the utilization of renewable energy rather than the conventional energy if its available.

3 DUAL-LEVEL OPTIMIZATION

In this section, the hierarchical dual-level optimization problem is discussed

3.1 Dynamic Model

The objective of achieving an efficient energy dispatch for the MMGs network within hierarchy optimal control based on distributed MPC framework,

Based on (1) and (13) we have the following dynamic model the ith subsystems

$$\begin{aligned}x_i(k+1/k)&=a_ix_i(k/k)+b_iu_i(k/k)\\ y_i(k/k)&=c_iu_i(k/k)\end{aligned} \quad (15)$$

Where
$$\begin{aligned}x_i(k/k)&=[E_i^b(k),],\\ u_i(k/k)&=[P_i^{SL}(k),P_{surp}(k),P_i^{DG}(k),E_i^{ch}(k),\\ &\quad E_i^{dch}(k)]\\ y_i(k/k)&=[P_i^m]\end{aligned}$$

Note that the matrices a_i,b_i,c_i,d_i are the states, inputs, and output matrices, the optimization over the control horizon is given by the following:

$$x_i(k)=[x_i(k+1/k),x_i(k+2/k),....,x_i(k+N/k)]$$

$$u_i(k)=[u_i(k/k),u_i(k+1/k),....u_i(k+N-1/k)]$$

3.2 Upper Level: DSO optimization:

The main objective of the DSO is to guarantee optimal operating cost and efficient energy management for the MMGs. The reference power profile P_i^{REF} is computed as the solution for the economic optimization problem (16) , In particular, define as

$$\begin{aligned}J_i^{ref}(k)=\min\sum_{l=l}^{N}\sum_{i=1}^{M}\xi_1(P_i^{CL}(k+l/k))-P_i^{RES}(k+l/k))\\ +\xi_2C_i^b(P_i^b(k+l/k))+\xi_3C_i^{DG}(P_i^{DG}(k+l/k))\\ +\xi_4C_{cur}(P_i^{SL}(k+l/k))\end{aligned} \quad (16)$$

subject to

- the satisfaction of following constraints: batteries (2), loads (5)-(6), DGs (8)-(10), and RES (12)
- the dynamic model (13), and operation cost of each unit (3), (7), (11).

where ξ_1,ξ_2,ξ_3,ξ_4 related to the weighting coefficient, the above optimization guarantees the demand-supply for the

MMGs system while reducing the operating cost, we defined P_i^{REF} as the optimal solution of (16).

3.3 *Lower level: (re-optimization): local controller*

the computed optimal reference plan from the DSO higher level is imposed as tracking setpoint solution P_i^{ref} by re-scheduling the active controllable loads and batteries charging and discharging as follows

$$J_i(k)=\sum_{l=1}^{N}(P_i^{SL}(k+l/k)-P_i^{ref}(k+l/k)) \\ +(E_i^{ch}(k+l/k)-E_i^{dch}(k+l/k)) \tag{17}$$

subject to

- the satisfaction of constraints on total active scheduled power (6), and constraints on DGs (8)-(10)
- the dynamic power balance (13)

3.4 *The hierarchical Dual-level EMS-MPC*

The flowchart in Fig. 2 demonstrate the hierarchical dual-level optimization framework with DSO as the upper level and local as a lower layer. The DOS receives the information data form each microgrid, at the same time MMGs exchange information between each other, the DSO solves the energy dispatch problem based on minimization of global operating cost, and provide a reference power scheduling. In the next step, the tracking setpoint calculated in the upper level is sent to the local controller, in this stage LC re-schedule the emery dispatching while coordinating between each other and exchange the power surplus

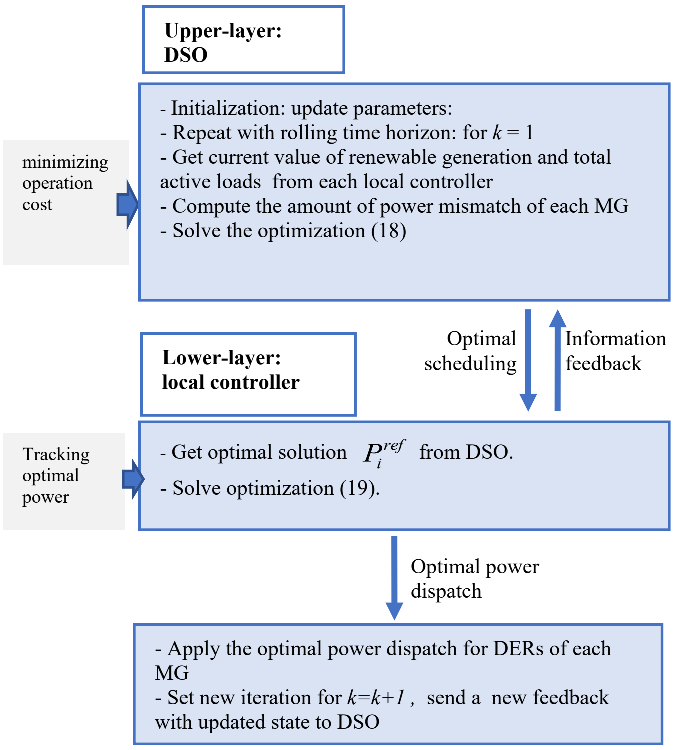

Fig. 2. Flowchart of the hierarchical dual-level optimization

4 CONVERGENCE AND STABILITY

Dynamic model (15) can be defined stable, if the following conditions are satisfied; the existence of $P>0$ with $P^T=P$ and $V_i(k)=x_i^T(k)P_ix_i(k)$ as and positive-definite quadratic Lyapunov function such that $V_i(k+1)-V_i(k)<0$.

Let's define an upper bound $V_i(k/k)\le\gamma_i(k)$ on the above performance index, is obtained following, for $l=0$ to $l=\infty$ we have

$$J_{i,\infty}(k)\le\gamma_i(k) \tag{18}$$

Given the assumption that the x^* is the initial solution $P_i(k,l),P_i(k,n)$ and $P_i(k,1),P_i(k+1,n)$ are optimal at a time interval k and, respectively $k+1$. Then by substituting (18) with $n=0$ to $n=\infty$ and $l\ge N-1$ we get

$$V_i(k/k)\big((x_i(k+1/k+1),P_i(k+1,l),P_i(k+1,n)\big) \\ -V_i(k/k)\big((x_i(k),P_i(k,l),P_i(k,n)\big)\le 0 \tag{19}$$

Since the $\gamma_i(k)$ is the upper bound of the MPC optimization problem, that means that $J_i(k)$ is bounded such that $J_i(k)<V_i(k)<\gamma_i(k)$, from robust MPC, see (Mayne et al. 2005), the index function is non-increasing. Thus, the algorithm convergence is guaranteed.

5 SIMULATION AND ANALYSIS

A scenario of three cooperative microgrids connected to the DSO illustrated in Fig. 3. We used a real load demand data from US energy department DOE of three commercial buildings, solar-PV and wind generation from ELIA electricity operators (Datasets - OpenEI DOE Open Data.; Solar-PV, (2020), and wind power generation, (2020))

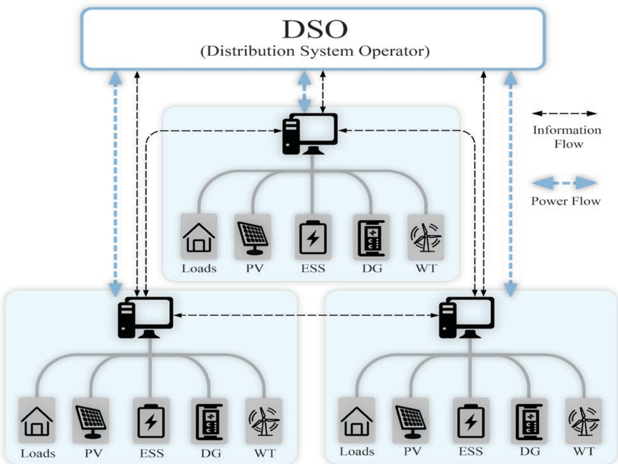

Fig. 3. Illustration of studied MMGs

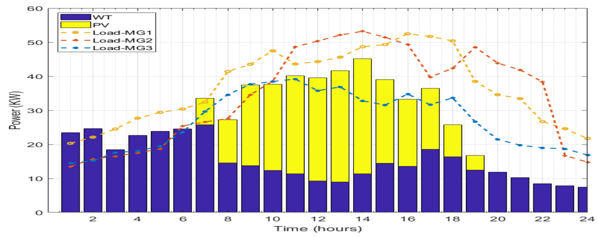

Fig.4. Forecasted Load and RESs generation for a typical day

each microgrid associated with: Load, PV, WT, ESS, and DG. For the simulation time horizon is 24 h, parameters summarized as follow:

$$E_{SOC,i}^{chrg} = 40, E_{SOC,i}^{disch} = 5, \overline{P}_i^{RES} = 60, \overline{P}_i^{gen} = 45$$

Figure.4. shows three MGs demand load and RES power production. In Fig. 5. Illustrate optimal energy dispatching with the proposed approach, for example, in MG2 from 11 am to 3 pm, we notice that due to insufficient RESs generation, the surplus energy from MG3 is used to keep supply-demand balance. In Fig. 6 .shows the charging and discharging of batteries of each MG.Fig.7. DGs power output is simulated with our approach compared to independent optimization. The result shows that the cooperative dual-level strategy is reducing the usage of power from the diesel generators due to the advantage of the surplus energy sharing strategy between MGs.

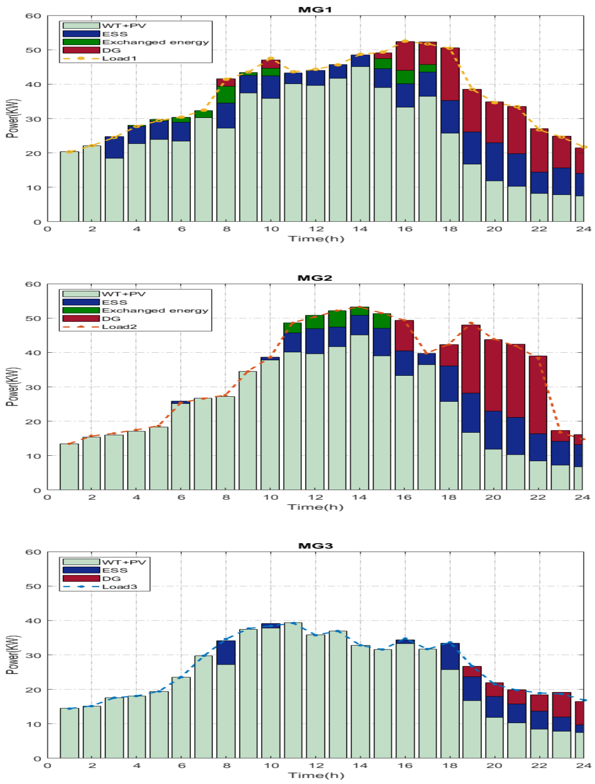

Fig.5 . Energy dispatch and scheduling with cooperative dual-level distributed MPC optimization.

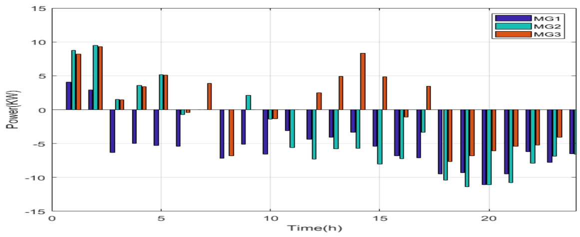

Fig.6 Charging -Discharging of each MG

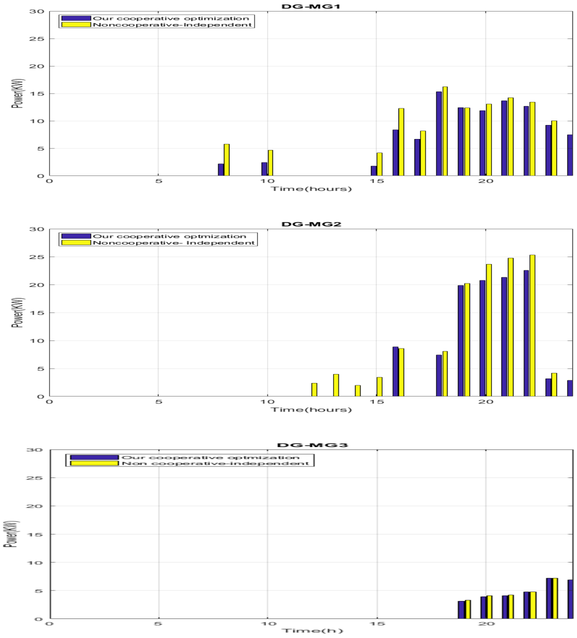

Fig.7. DGs power output in MG1 and MG2 our cooperative approach and noncooperative-independent optimization

The operating costs of each MGs presented in table 1 and Fig. 8 and Fig. 9. The fuel cost is 42 ¥/kW; we assumed that the maintenance cost is 2.4 ¥. Noting that currency (¥) corresponds to the Chinese Yuan. We compared our approach with independent optimization based on robust MPC for the operating cost of each microgrid; the results show a significant decrease in global costs with our strategy. Thus, we verified the advantage of our approach in terms of costs and saving.

Table 1: Total operating cost

Total cost (¥)	MG 1	MG 2	MG 3
Cooperative optimization	8164.3	7228.3	3987.4
Noncooperative optmization	13878.3	9072.6	7341.7

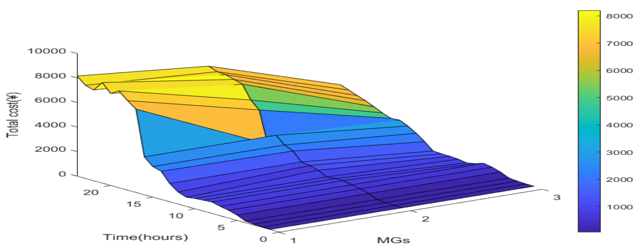

Fig.8 . Total operating cost with our approach

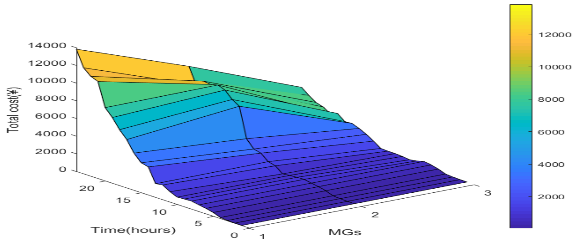

Fig.9 . Total operating cost with noncooperative optimization

6 CONCLUSION

In this paper, an optimal optimization strategy is proposed for the new generation of cooperative microgrids networks based on hierarchal dual-level Model Predictive Control for cooperative MMGs operated in islanded mode, with distribution system operator DSO as upper-level optimization for minimizing the global operating cost and in the other hand the local controller as a lower level to track the reference plan from DSO. The main objective of this hierarchical approach is to achieve an efficient economic dispatch along with cost operating reductions for neighboring microgrids. The proposed policy shows the effective use of renewable energy resources, and a mathematical model is employed to solve energy management in an autonomous optimization. The forecasted energy dispatch proves the effectiveness of the cooperative distributed algorithm framework compared to noncooperative optimization, to track the supply-demand target. Hence, it can conclude that the proposed approach achieves optimal energy management in the coordinated microgrids system. Future works can follow this paper by considering the renewable generation uncertainty by data-driven processing strategies, and dynamic pricing for smart microgrids in public grid-connected mode.

REFERENCES

Brahmia, I, Zhao, P., and Wang, J., (2019, December). "Efficient Energy Management of Multi-Microgrids Systems Based on Distributed Cooperative Control in Autonomous. In press. *ICPES, 9th International Conference on Power and Energy Systems*.

Datasets - OpenEI DOE Open Data. *https://openei.org/doe-opendata/dataset?sectors=buildings* .(accessed 14 April 2020)

Hajar, K., Hably, A., Bacha, S., Elrafhi, A., & Obeid, Z. (2016, October). An application of a centralized model predictive control on microgrids. In *2016 IEEE Electrical Power and Energy Conference (EPEC)* (pp. 1-6). IEEE.

Ju, C., Wang, P., Goel, L., & Xu, Y. (2017). A two-layer energy management system for microgrids with hybrid energy storage considering degradation costs. *IEEE Transactions on Smart Grid*, *9*(6), 6047-6057.

Legry, M., Colas, F., Saudemont, C., Dieulot, J. Y., & Ducarme, O. (2018, October). A Two-layer Model Predictive Control Based Secondary Control with Economic Performance Tracking for Islanded Microgrids. In *IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society* (pp. 77-82).

Mayne, D. Q., Seron, M. M., & Raković, S. V. (2005). Robust model predictive control of constrained linear systems with bounded disturbances. *Automatica*, *41*(2), 219-224.

Mehrizi-Sani, A. (2017). Distributed control techniques in microgrids. In *microgrid* (pp. 43-62). Butterworth-Heinemann.

Minchala-Avila, L. I., Garza-Castañón, L. E., Vargas-Martínez, A., & Zhang, Y. (2015). A review of optimal control techniques applied to the energy management and control of microgrids. *Procedia Computer Science*, *52*(1), 780–787.

Nandar, A., & Supriyadi, C. (2013). Robust PI control of smart controllable load for frequency stabilization of microgrid power system. *Renewable Energy*, *56*(C), 16-23.

Papavasiliou, A., Mou, Y., Cambier, L., & Scieur, D. (2017). Application of stochastic dual dynamic programming to the real-time dispatch of storage under renewable supply uncertainty. *IEEE Transactions on Sustainable Energy*, *9*(2), 547-558.

Parisio, A., Rikos, E., & Glielmo, L. (2014). A model predictive control approach to microgrid operation optimization. *IEEE Transactions on Control Systems Technology*, *22*(5), 1813-1827.

Parisio, A., Rikos, E., Tzamalis, G., & Glielmo, L. (2014). Use of model predictive control for experimental microgrid optimization. *Applied Energy*, *115*, 37-46.

Parisio, A., Wiezorek, C., Kyntäjä, T., Elo, J., Strunz, K., & Johansson, K. H. (2017). Cooperative MPC-Based Energy Management for Networked Microgrids.

Rezaei, N., & Kalantar, M. (2015). A novel hierarchical energy management of a renewable microgrid considering static and dynamic frequency. *Journal of Renewable and Sustainable Energy*, *7*(3), 033118.

Sachs, J., & Sawodny, O. (2016). A two-stage model predictive control strategy for economic diesel-PV-battery island microgrid operation in rural areas. *IEEE Transactions on Sustainable Energy*, *7*(3), 903-913.

Solar-Pv power generation data *https://www.elia.be/en/grid-data/power-generation/solar-pv-power-generation-data* (accessed 13 april 2020)

Venayagamoorthy, G. K., Sharma, R. K., Gautam, P. K., & Ahmadi, A. (2016). Dynamic energy management system for a smart microgrid. *IEEE transactions on neural networks and learning systems*, *27*(8), 1643-1656.

Wind- power generation data *https://www.elia.be/en/grid-data/power-generation/wind-power-generation* (accessed 13 april 2020)

Zhai, M., Liu, Y., Zhang, T., & Zhang, Y. (2017, December). Robust model predictive control for energy management of isolated microgrids. In *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 2049-2053).