Chance-constrained models for transactive energy management of interconnected microgrid clusters

Daneshvar, Mohammadreza ; Mohammadi-Ivatloo, Behnam ; Asadi, Somayeh ; Anvari-Moghaddam, Amjad; Rasouli, Mohammad ; Abapour, Mehdi; B. Gharehpetian, Gevork

Published in:
Journal of Cleaner Production

DOI (link to publication from Publisher):
https://doi.org/10.1016/j.jclepro.2020.122177

Publication date:
2020

Document Version
Accepted author manuscript, peer reviewed version

The Chance-Constrained Models for Transactive Energy Management of Interconnected Microgrids Clusters

Mohammadreza Daneshvar[a], Behnam Mohammadi-ivatloo[a], Somayeh Asadi[b], Amjad Anvari-Moghaddam[c,a], Mohammad Rasouli[d], Mehdi Abapour[a], Gevork B. Gharehpetian[e]

E-mails: M.r.daneshvar@ieee.org; bmohammadi@tabrizu.ac.ir; asadi@engr.psu.edu; aam@et.aau.dk; mur37@psu.edu; abapour@tabrizu.ac.ir; grptian@aut.ac.ir

[a]Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran

[b]Department of Architectural Engineering, Pennsylvania State University, Pennsylvania, USA

[c]Department of Energy Technology, Aalborg University, 9220 Aalborg East, Denmark

[d]Penn State Erie, The Behrend College, Erie, PA 16563, USA

[e]Faculty of Electrical Engineering, Amirkabir University of Technology, Tehran, Iran

Abstract

Transactive energy as an emerging approach and sustainable technology can provide an exceptional opportunity for microgrids to exchange energy with each other for greater benefits in the cluster mode. In this mode of operation, some collective and individual interests can be realized for the microgrids based on transactive energy management. This paper proposes mathematical models for microgrid clusters using a transactive energy structure to manage energy exchange in the smart grid. In order to make an informed decision for the operation of microgrid clusters, chance-constrained programming is employed to consider the uncertainties in balancing collective and individual interests under the transactive energy management. In this research, sixteen commercial microgrids are considered in the process of evaluating the efficiency of the proposed models using the chance-constrained programming method. Simulation results prove the effectiveness of the transactive energy approach accompanying the implementation of chance-constrained programming in energy management of the microgrid clusters.

Keywords Transactive energy, chance-constrained programming, microgrid clusters, smart grid, energy management, uncertainty handling

Nomenclature

Abbreviations

CCHP	Combined cooling, heating and power
CCP	Chance-constrained programming
CDFs	Cumulative density functions
DERs	Distributed energy resources
FFR	Fast Forward Reduction
iCDF	Inverse cumulative distribution functions
LHS	Latin hypercube sampling
LTM	Local transaction market
PGU	Power generation unit
RERs	Renewable Energy Resources
SRS	Simple random sampling

Indices

m	Index of microgrids.
ω	Index of scenarios.
t	Index of time.

Parameters

$tCLO_{m,t}$ / $tHLO_{m,t}$	The cooling/heating energy load in microgrid *m* at time *t*.
η_{tSc} / η_{tSd}	The charging/discharging efficiency of thermal storage.
ItS	The initial stored thermal energy in thermal storage.
eL^{Max} / cL^{Max} / hL^{Max}	The maximum amount of electrical/cooling/ heating energy trading in the LTM.
eM^{Max}	The maximum amount of energy trading between microgrids with the main grid.
$\gamma_{B\min}$	The minimum storage limit coefficient of battery.
$\gamma_{Ts\min}$	The minimum storage limit coefficient of thermal storage.
l	The number of random variables in the CCP model.
$\Pr_{\omega}$	The probability of scenario ω.
η_C / η_H	The thermal efficiency of cooling/heating component.
φ	The user-defined confidence level

Variables

$CLtM_{m,t}$ / $HLtM_{m,t}$	The cooling/heating energy transmitted from LTM to microgrid *m* at time *t*.
$CMtL_{m,t}$ / $HMtL_{m,t}$	The cooling/heating energy transmitted to the LTM from microgrid *m* at time *t*.
$XCin_{m,t}$ / $XCout_{m,t}$	The cooling energy transmission/ contribution state of microgrid *m*.
$tSc_{m,t}$ / $tSd_{m,t}$	The charging/discharging rate of thermal storage.
$XtSc_{m,t}$ / $XtSd_{m,t}$	The charging/discharging state of thermal storage in microgrid *m* at time *t*.
$eBd_{m,t,\omega}$ / $eBc_{m,t,\omega}$	The discharging/ charging rate of the battery storage.
$XBd_{m,t,\omega}$ / $XBc_{m,t,\omega}$	The discharging/charging state of battery storage in microgrid *m*.
$eNtM_{m,t,\omega}$	The electrical energy purchased from the power grid by microgrid *m*.
$eMtN_{m,t,\omega}$	The electrical energy sold to the power grid by microgrid *m*.

$\gamma_{Bc\min} / \gamma_{Bd\min}$	The coefficient for minimum charging/discharging limit of a battery storage.	$ePGU_{m,t,\omega}$	The electricity generated by PGU in microgrid *m*.
$\gamma_{Bc\max} / \gamma_{Bd\max}$	The coefficient for maximum charging/discharging limit of a battery storage.	$ePV_{m,t,\omega}$	The electricity generated by solar PV panel in microgrid *m*.
$\gamma_{Tsc\min}$ / $\gamma_{Tsd\min}$	The coefficient for minimum charging/discharging limit of a thermal storage.	$eLtM_{m,t,\omega}$	The electricity transmitted from LTM into microgrid *m*.
$\gamma_{Tsc\max}$ / $\gamma_{Tsd\max}$	The coefficient for maximum charging/discharging limit of a thermal storage.	$eMtL_{m,t,\omega}$	The electricity transmitted to LTM from microgrid *m*.
$\alpha_{pgu}, \beta_{pgu}$	The coefficients of fuel to electricity conversion of PGU.	$XEin_{m,t}$ / $XEout_{m,t}$	The electricity transmission/ contribution state of microgrid *m*.
η_{Bd} / η_{Bc}	The discharging /charging efficiency of the battery storage.	$Fbo_{m,t}$	The fuel consumed by the boiler unit.
Δt	The decision time interval.	$Fpgu_{m,t,\omega}$	The fuel consumed by the PGU.
$eLO_{m,t}$	The electrical energy load.	$XHin_{m,t}$ / $XHout_{m,t}$	The heating energy transmission/ contribution state of microgrid *m*.
η_{bo}, η_{pgu}	The efficiency of boiler and fuel to thermal conversion of PGU.	$Xpgu_{m,t,\omega}$	The ON or OFF state of PGU in microgrid *m*.
$pNtM_{t,\omega}$	The electricity purchasing price for microgrids.	$eB_{m,t,\omega}$	The stored electrical energy in battery storage in microgrid *m*.
$pMtN_{t,\omega}$	The electricity selling price for microgrids.	$tES_{m,t}$	The stored thermal energy in thermal storage in microgrid *m*.
pBO_t	The fuel price for boiler at time *t*.	$tEcS_{m,t}$ / $tEhS_{m,t}$	The thermal energy into the thermal storage from cooling/heating process.
$pPGU_t$	The fuel price for PGU at time *t*.	$tECc_{m,t}$ / $tEHc_{m,t}$	The thermal energy provided to cooling/heating component.
IeB	The initial stored electricity in battery storage.	$tECCS_{m,t}$	The thermal energy provided to thermal storage from the CCHP system.
EPL_t	The electrical energy price in the LTM.	$tESCc_{m,t}$ / $tESHc_{m,t}$	The thermal energy transmitted to cooling/heating component from thermal storage.
HPL_t	The heating energy price in the LTM.	μ	The percentage of cost-saving of microgrids in Model IV.
CPL_t	The cooling energy price in the LTM.	x	The vector of decision variables
θ	The satisfactory level of individual interests in Model III.	ξ	The vector of *K* random variables

1. Introduction

Transactive energy is an intriguing subject in the energy market today to balance energy resources in ways we have not done before. Transactive energy improves the way we use power, facilitates the integration of intermittent renewable energy and improves power grid reliability (Daneshvar et al., 2020). In this regard, operation of the high level of Renewable Energy Resources (RERs) for clean energy production is considered as a priority research topic (Sedighizadeh et al., 2018) due to significant advantages of them such as reducing energy production cost and mitigating greenhouse gas emissions (Shezan et al., 2016). Microgrids, as essential components of future power grid especially in the integration of RERs (Prathapaneni and Detroja, 2019), can serve as transactive energy agents to provide beneficial solutions to the electricity utilities at distribution levels, and to the power system at large scale (Rahimi et al., 2016). Additionally, a more reliable power supply can be realized in both autonomous islanding and grid-connected as the two modes of the operation of these systems (Justo et al., 2013). In this industrial landscape, advanced emerging technologies integrated with a transactive energy network allow the interconnected operation of microgrids (Prinsloo et al., 2018). This leads to greater energy efficiency along with some collective and individual interests under the cluster mode of communication (Bazmohammadi et al., 2019b). For instance, in (Moayedi and Davoudi, 2015) a distributed control mechanism manages the power-sharing between the microgrids within a cluster, which reduces the maintenance cost, improves the system reliability and availability, and increases the overall lifespan of the network. Moreover, multiple interconnected microgrids are considered in (Utkarsh et al., 2018) for developing an efficient strategy for energy exchanging and scheduling of internal smart devices. Based on the developed strategy, each microgrid aims not only to manage the internal devices, but also to optimize its energy trading to gain benefits. To obtain the mentioned objectives, the authors propose computational intelligence-based algorithm and distributed model predictive and simulation results are analyzed based on the different scenarios. A theoretical framework is proposed by Wang *et al.* in (Wang and Huang, 2016) to efficiently explore the various RERs for the cooperative planning in interconnected microgrids. Total system cost is minimized based on the proposed framework and due to the behaviors of microgrids, the fair cost sharing method is also designed to provide benefits for all microgrids from the cooperative framework. To well manage energy production and consumption in presence of RERs, the authors in (Lu et al., 2017) propose a two-level optimization model for the energy control between the microgrid clusters and distribution systems. The operation of the distribution network is considered in the upper level, while the coordinated operation of microgrids is investigated at the lower level. The modified hierarchical genetic algorithm is applied to solve the model and the interactive game matrix is also employed to organize the energy trading between the microgrids and distribution network.

Currently, one major research direction in the microgrid area is optimal energy management using emerging technologies that can control and manage the energy exchange and load sharing in the smart grid with high penetration of distributed energy resources (DERs). For example, a deterministic energy management system is proposed in (Kanchev et al., 2011), which consists of a PV system along with a gas microturbine and embedded storage systems, for business customers of a microgrid in the smart grid. Also, Le Anh *et al.* propose a hierarchical distributed predictive control approach for energy management in microgrids with the aim of providing an innovative and comprehensive framework to maximize their benefits (Dehghani-Pilehvarani et al., 2019). With the widespread presence of RERs in the grid, distributed economic dispatch and robust energy demand management are considered in (Zhang et al., 2013) for the grid-connected mode of microgrids with high RERs penetration. Because of uncertainties in the energy produced by RERs, establishing an energy balance between supply and demand has become more challenging. Thus, in order to assess the supply-demand gap in (Nunna and Doolla, 2014), an intelligent agent-based framework is applied for demand-side energy management in multi-microgrids with virtual market environments structure. In addition to the aforementioned studies, a hierarchical power scheduling method is investigated in (Bazmohammadi et al., 2019a; Wang et al., 2015) to optimally manage the power exchange, distribution and storage in the power grid with cooperative microgrids. Zhao *et al.* present an optimal solution for resource management problems by enhancing the coordination and communication based on the multi-agent framework for microgrids in (Zhao and Ding, 2017). In (Wang et al., 2017), a classical two-stage stochastic programming model is employed to control the local energy generation and demand in the presence of intermittent RERs with uncertainty, where modeling of the arbiter's problem and the agent decision problems are considered as the first-stage master problem and second-stage subproblems, respectively. An energy management and control system in the presence of hybrid energy resources such as solar and wind is presented in (Merabet et al., 2016) for a laboratory-scale microgrid. In this system, various control configurations are also tested on the proposed microgrid with open-architecture platform. In (Dehghanpour and Nehrir, 2017), an agent-based hierarchical model is suggested for power management in a distribution system with several microgrids. This research is accomplished in the lowest and highest levels of the proposed model to consider optimal energy pricing.

In addition to the reported research studies on multiple microgrids, the benefits of microgrid clusters are also discussed in the literature. For example, the self-organized property of microgrid cluster to guarantee energy efficiency and reliability of sensitive loads after extreme events in the isolated mode of microgrid cluster is investigated in (He and Giesselmann, 2015). Moreover, the work reported in (Marvasti et al., 2014) introduces a hierarchical bi-level decision framework to coordinate energy trade among the distribution grid and microgrid clusters along with the optimal operation of these types of microgrids. The potentials of transactive energy for optimal operation and energy management of microgrids is also investigated in (Nunna and Srinivasan, 2017), where an agent-based framework is proposed to solve the aggregated complexity created by microgrids with comprehensive energy management in distribution systems. One of the shortcomings of the current research studies is that the uncertainties in some parameters under various scenarios along with realistic conditions of operation are not properly considered in the energy management of microgrid clusters with a transactive energy paradigm.

In this paper, optimal scheduling of the cooperative microgrids is carried out by proposing the four operational models for microgrids in the cluster mode. The transactive energy concept is applied to multiple microgrids in order to manage and control energy exchange effectively. The overall structure of this research is shown in Fig. 1.

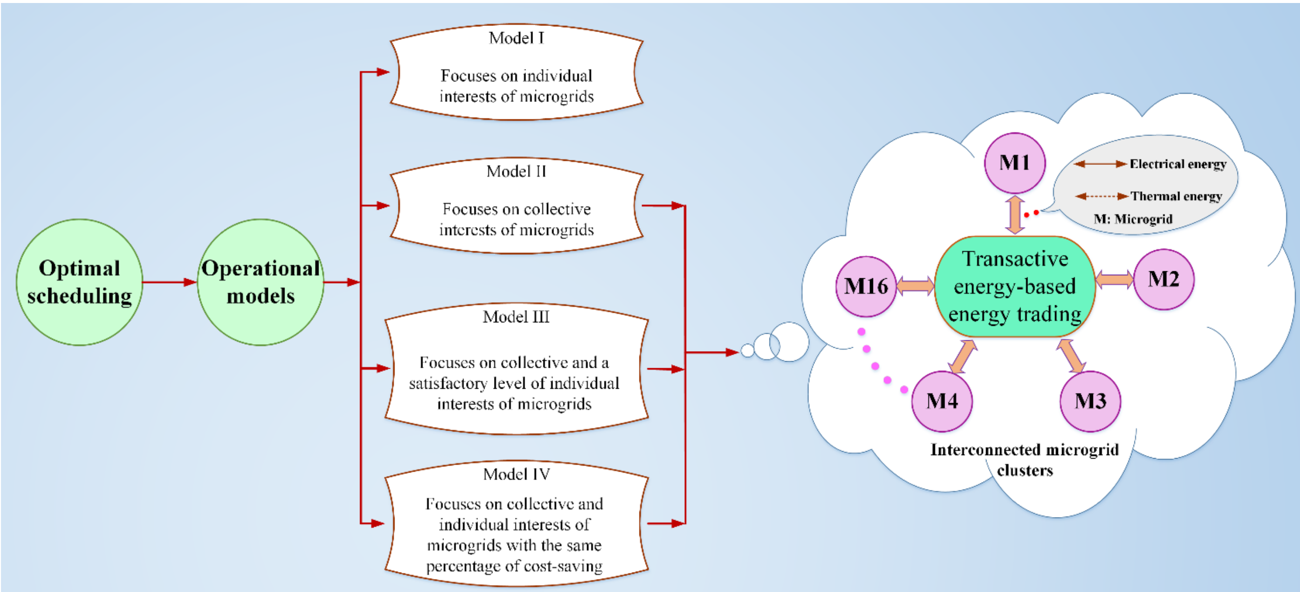

Fig. 1. The overall structure of this research

According to Fig. 1, four decision-making scenarios (Models I-IV) are proposed for energy management of microgrid clusters with some collective and individual interests based on the transactive energy concept. In this framework, each microgrid can trade energy with other microgrids and with the power grid based on the new proposed models. In this research, minimizing the total energy cost is assumed as a collective interest for the cluster and maximizing the relative amount of cost savings is also considered as individual interest. Model I, proposed in this paper, aims at evaluating the energy exchange in a way to maximize the individual interests where microgrids do not trade energy among themselves. Model II focuses on maximizing the collective interests, in which microgrids can exchange energy with each other to reduce their energy costs. Model III, on the other hand, considers both individual and collective interests so that a satisfactory level of individual interests is targeted to be satisfied in the microgrid clusters. Models IV is able to maximize individual interest as well as collective interests. Indeed, this model realizes the same percentage of cost savings in the energy exchanging process. For this study, sixteen commercial microgrids located in the Chicago area are intended, which the possibility of the electrical and thermal energy trading is provided for them based on the transactive energy paradigm. The chance-constrained programming (CCP) as an optimization tool is effectively applied not only to consider realistic conditions of the problem but also to achieve certain objectives. In this respect, Latin hypercube sampling (LHS) and fast forward reduction methods are used for scenario generation and reduction, respectively.

The contributions of this paper are described as follows:

- Energy exchanging, control, and management between microgrids are effectively considered by proposing the various operational models to provide both the individual and collective interests simultaneously for the participated microgrids in the local energy trading market.
- The transactive energy concept is applied in structuring some of the operational models not only to reduce the system dependency to the main grid but also to provide the same percentage of cost-saving for the microgrids.
- The CCP method is employed for modeling some existing uncertainty parameters along with considering the realistic condition of a problem for applying this research to the large-scale practical cases.

The remainder of this paper is organized as follows. Section II provides the general theory behind the CCP, LHS method, and fast forward reduction technique. Section III drives the modeling framework for microgrid clusters. The operation decision models for transactive energy management are presented in Section IV. Section V shows the numerical results of the proposed models for microgrid clusters. Finally, Section VI concludes the paper.

2. Background and assumptions

2.1. Chance-constrained programming (CCP)

Stochastic programming and CCP are two popular tools that can be employed as probabilistic optimization methods to manage random uncertainties (Marino et al., 2018). Chance-constrained optimization is stochastic programming that uses probabilistic measures over the constraints with uncertainty parameters (Frick et al., 2019). Indeed, for risk-based decision making, this approach is deemed as a typical model for stochastic programming. The CCP technique is an effective way to capture the fluctuations of different uncertain parameters, which are intended as the random variables and are modeled using the related probability density functions. This approach has several remarkable advantages that attempt to reconcile optimization over uncertain constraints (Schwarm and Nikolaou, 1999). Based on this method, a stochastic programming model can be converted to the equivalent deterministic one while the CCP facilitates the incorporation of the stochastic programming with other uncertain optimization techniques such as fuzzy mathematical programming (Huang et al., 2012). The CCP method enables the objective function to be maximized or minimized subject to constraints with uncertain parameters and specified predetermined confidence levels. The decision-makers can determine these confidence levels as appropriate safety margins. Indeed, the decision-makers can adopt the optimal strategies by receiving valuable information from the CCP approach regarding the tradeoffs between the prescribed level of probability and the objective function's tolerance values of the constraints (Chen et al., 2013). On the other hand, the CCP method is incorporated with the scenario generation methods for probabilistic evaluating the problem considering various states of the uncertain parameters' occurrence. Generating numerous scenarios in the CCP is a useful way for considering almost all occurrence states of the uncertain parameters and for realistic modeling of the system. However, evaluating a large set of scenarios could be complex and time-consuming, which brings high computational burdens accordingly making such algorithms inappropriate for practical problems. In addition to the aforementioned disadvantages, the CCP method cannot provide robust conditions for the systems that face a high level of uncertainties in the presence of numerous RERs. However, in this paper, the CCP method is used accompanying the scenario reduction approach for reducing the number of generated scenarios to overcome the challenges regarding the complexity, high computational burden, and time-consuming caused by a large number of scenarios. Generally, a CCP problem can be defined as follows:

$$\min_{x} f(x, \xi) \tag{1}$$

$$\text{Subject to: } \Pr\{g_i(x, \xi) \geq 0, \ \ i = 1, \cdots, k\} \geq \varphi \tag{2}$$

where, $f(x, \xi)$ is the objective function, which typically contains random variables, x is the vector of decision variables and ξ presents the vector of K random variables with the cumulative density functions (CDFs) $F_{\xi_l}(z) = \Pr(\xi_l \leq z)$ $(l = 1, \cdots K)$. Equation (2) describes the set of joint probabilistic constraints in which probability measure is denoted by Pr(), and the set of constraints is denoted by $g_1, \cdots, g_k$ which includes random variables. The parameter φ is a user-defined confidence level applied to the probabilistic constraints. In another word, the probability of satisfying the equations with uncertainty parameters is considered to be greater than φ % in the presence of the stochastic behaviors of the uncertainty parameters. Indeed, at least, the φ % of the generated scenarios for the uncertainty parameters should satisfy the related equations in the CCP method. Therefore, the amount of parameter φ is intended to be equal to 90 % for this research i.e. only 10% of generated scenarios are allowed to violate the related constraint with the aim of considering the probabilistic nature of the problem based on the CCP method. The probability of k individual constraints is defined using the joint probability. Through considering the joint distribution of ξ, a multidimensional integral can be used to directly find the solution to the joint CCP problem. Nevertheless, the non-convex solution space created by inappropriate numerical processing of multidimensional integration is a basic problem for this method. Hence, generating a set of individual chance constraints from the decomposition of the joint chance constraint is considered to find the solution to the CCP problem (Mühlpfordt et al., 2018). The complete descriptions and model of the CCP approach can be found in (Hajian et al., 2012).

2.2. Latin Hyperbolic Sampling method (LHS)

In order to solve the probabilistic problems such as probabilistic power flow in the power system, Monte-Carlo simulation and simple random sampling (SRS) are utilized, but the large computational burden is a basic drawback of this method (Fioriti and Poli, 2019). The LHS is one of the powerful stratified sampling methods for scenario generation. This approach is more robust and can cover a large number of input random variables in a large sampling space compared to the SRS method for the same sample size (Chen et al., 2012). The key principles of LHS can be found in (Yu et al., 2009).

2.3. Fast Forward Reduction method (FFR)

In power systems, multistage stochastic programs are applied often in modeling risk management problems. All generated scenarios and corresponding probabilities are taken into account in the multivariate random data process. In practical problems, considering all scenarios will lead to computational complexity and a time-consuming solution. Because of the time limitation of such problems, considering all scenarios in solving the problem is not practical (Dolatabadi and Mohammadi-Ivatloo, 2017). Thus, choosing candidate scenarios among the generated scenarios would be essential for such problems. Therefore, scenario reduction methods are proposed for the scenario-based problems. The most effective one is the fast forward reduction method. Algorithm 1 presents the complete process of the fast forward reduction method in reducing the number of generated scenarios (Wu et al., 2007).

Regarding this algorithm, let $\psi_{\omega}(\omega: 1,...,N_{\omega})$ indicate N_{ω} different scenarios, which $\Pr_{\omega}$ presents the probability of scenario ω. $DS_{\omega,\omega'}$ denotes the distance of scenario pair (ω,ω').

Algorithm 1 Scenario reduction process using the fast forward reduction method

Step 1:	Set Φ is the initial set of scenarios; DR states the scenarios to be deleted so that the initial DR are null. Compute the distances of all scenario pairs: $DS_{\omega,\omega'} = DS(\psi_{\omega},\psi_{\omega'})$; $\omega,\omega' = 1,...,N_{\omega}$
Step 2:	For each scenario κ, compute $PR_{\kappa}(\upsilon) = \sum_{\omega' \neq \kappa} \Pr_{\omega'}.DS(\psi_{\omega'},\psi_{\kappa})$; $\kappa = 1,...,N_{\omega}$; υ is the scenario index that has the minimum distance with scenario κ. Choose ℓ so that $PR_{\ell} = \min\ PR_{\kappa}$, $\kappa = 1,...,N_{\omega}$
Step 3:	$\Phi = \Phi - \{\ell\}$, $DR = DR + \{\ell\}$; $\Pr_{\upsilon} = \Pr_{\upsilon} + \Pr_{\ell}$;
Step 4:	Repeat steps 2 to 4 until the number of scenarios to be deleted meets the target.

This approach works based on the Kantorovich distance theory. In other words, the distance of each scenario is computed with other scenarios and the candidate scenarios are selected from the scenarios with the minimum distance to the other scenarios (Steps 1 and 2). In this process, the probability of the selected scenarios is updated by adding the probability of the corresponding deleted scenarios to the previous probability of the selected scenario (Step 3). Detailed information on this approach is presented in (Wu et al., 2007) and (Keyvanloo et al., 2015).

3. Comprehensive operational modeling framework for microgrid clusters

3.1. System architecture for microgrids

In this study, sixteen commercial microgrids in a cluster together with the needed infrastructure for communications with the local transaction market (LTM) and power grid are considered. All components used in each of the microgrids and their relationships are illustrated in Fig. 2. Each microgrid is equipped with energy generation components, storage systems, and loads. In this research, combined cooling, heating and power (CCHP) as well as solar PV panels are assumed to be energy generation resources for each microgrid. In addition, electrical and thermal energy storage and their associated loads are also considered for each microgrid. The CCHP system is one of the more efficient devices in the microgrid structure (Yousefi et al., 2017) and it consists of two components, including power generation units (PGUs) and boilers. The PGU unit has a gas turbine for electricity generation. The heat energy output of this unit is utilized in the heat recovery process. The boiler unit in the CCHP system is used to compensate for the shortages of thermal energy through the conversion of gas fuel into heat. In this research, thermal load (heating and cooling energy demand) is met using the CCHP unit's output and thermal storage is also employed in each microgrid to increase the reliability of supplying thermal energy for the consumers (Mehrjerdi and Rakhshani, 2019). Indeed, it is assumed that each microgrid only is equipped with a CCHP unit as the system for providing the thermal demands of them. In addition, thermal energy trading along with electrical one is considered between the networked microgrids based on the transactive energy management that provides the free electrical and thermal energy trading for them without changing the transactive energy structure. In Fig. 2, the solid and dashed lines represent the electrical and thermal energy flow, respectively. Each microgrid is assumed to only trade electrical energy with the power grid, but they can exchange both electrical and thermal energy with LTM (other microgrids).

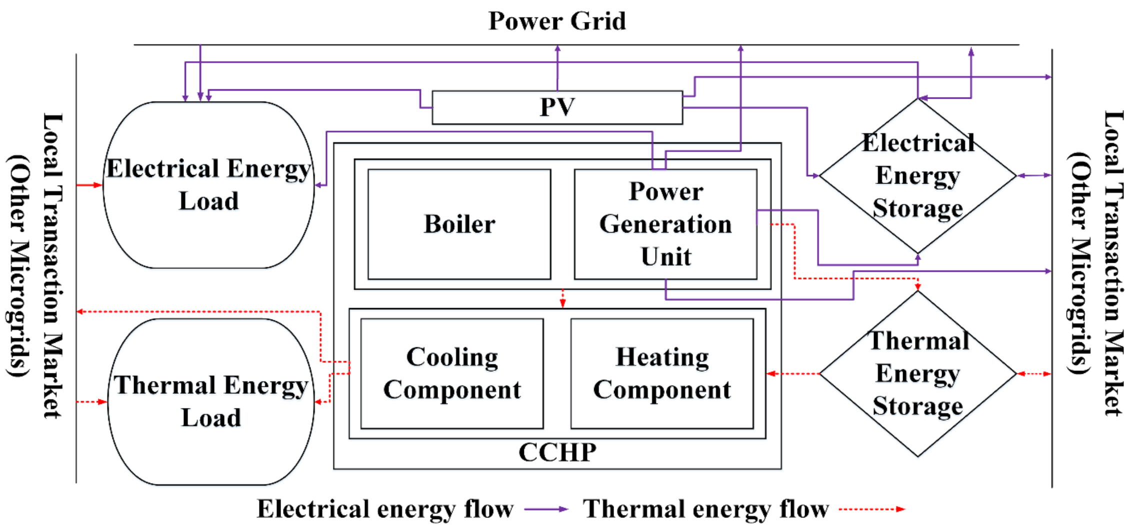

Fig. 2. Energy trading schematic of microgrid clusters with LTM

Moreover, transactive energy technology is employed for managing the energy trading between networked microgrids with each other and the power grid. Generally, transactive energy technology is defined by the GridWise Architecture Council as "a set of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter", which key value can become money or emission (Daneshvar et al., 2018a). In this paper, the potential of transactive technology is used in establishing the dynamic balance between electrical and thermal energy supply and demand with the aim of minimizing the energy cost of microgrid's cluster. Indeed, the LTM is created for providing free energy trading possibility for all microgrids to minimize the energy cost of them in the cluster based on the transactive energy technology. In this paper, the appropriate formulations are applied regarding the electrical and thermal dynamic energy balance in modeling the LTM for energy trading of microgrids (this is commensurate with the first part of the transactive energy definition i.e. “transactive energy technology … across the entire electrical infrastructure”). Moreover, the individual and collective benefits of the microgrids are investigated by proposing the four operational models which are also commensurate with the second part of the transactive energy definition, i.e. “…using value as a key operational parameter such as money”. Because of the existence of thermal energy demand along with electrical load in each microgrid, the proposed structure is developed to meet both the electrical and thermal energy demands to make it suitable for implementing on the practical cases. Therefore, focusing on the integrated electricity and heat system only is one of the accomplished steps in this research while proposing transactive energy-based energy trading models for the microgrids with considering their individual and collective benefits is the main goal of this study.

3.2. Mathematical models of microgrids

In this section, mathematical models of microgrid clusters including the objective function and constraints are presented.

3.2.1. Objective function

In this research, each microgrid is assumed to have only CCHP and PV as the primary energy production units to meet most of the local energy demand. The proposed transactive energy-based structure provides a suitable condition for the microgrids to meet the rest of their energy demand through the free energy trading in the LTM which subsequently postpones or reduces the need for capacity investment in microgrids. If none of the microgrids have the surplus energy for supplying to the LTM, they can receive the required energy from the power grid instead of LTM. It should be noted that a large portion of energy demand in each microgrid is provided by the CCHP units which add relatively high fuel costs to the microgrids operating costs. Hence, the energy cost of the microgrids could greatly affect their utility functions. Consequently, this study aims at minimizing the operation cost of each microgrid rather than maximizing their profits while satisfying operational constraints related to the power grid, LTM, and all components of a microgrid. This function has two terms; the first term represents energy trading cost between the power grid and microgrids, and the second term is associated with the fuel cost of PGU and boiler units. The objective function in this study is defined as follows:

$$\begin{aligned} F_m = & \sum_{\omega}\sum_{t} \Pr_{\omega}.(eNtM_{m,t,\omega}.pNtM_{t,\omega} - eMtN_{m,t,\omega}.pMtN_{t,\omega}) + \\ & \sum_{\omega}\sum_{t} (\Pr_{\omega}.Fpgu_{m,t,\omega}.pPGU_t + Fbo_{m,t}.pBO_t) \qquad \forall m \end{aligned} \tag{3}$$

where, F_m is the objective function for the microgrid *m*.

3.2.2. Constraints

Electrical energy received from the power grid and LTM and the electricity generated inside each microgrid should match the electricity leaving each microgrid plus the load. Thus, this constraint is expressed as follows:

$$\begin{aligned} & eNtM_{m,t,\omega} + ePV_{m,t,\omega} + ePGU_{m,t,\omega} + eLtM_{m,t,\omega} + eBd_{m,t,\omega}.\eta_{Bd} \\ & = eMtN_{m,t,\omega} + eLO_{m,t} + eMtL_{m,t,\omega} + \frac{eBc_{m,t,\omega}}{\eta_{Bc}} \quad \forall m, \forall t, \forall \omega \end{aligned} \tag{4}$$

In general, both the cooling and heating energy coming from different suppliers into a microgrid should be equal to the thermal energy demand and thermal energy coming out of each microgrid. These limitations are defined as follows:

$$(tECc_{m,t} + tESCc_{m,t}).\eta_C + CLtM_{m,t} = tCLO_{m,t} + CMtL_{m,t} + tEcS_{m,t} \qquad \forall m, \forall t \tag{5}$$

$$(tEHc_{m,t} + tESHc_{m,t}).\eta_H + HLtM_{m,t} = tHLO_{m,t} + HMtL_{m,t} + tEhS_{m,t} \qquad \forall m, \forall t \tag{6}$$

The fuel consumed by both PGU and boiler units in the CCHP system should not exceed their maximum capacities. These restrictions are written as:

$$Fpgu_{m,t,\omega} \le Xpgu_{m,t,\omega}.Spgu_m \qquad \forall m, \forall t, \forall \omega \tag{7}$$

$$Fbo_{m,t} \le Sbo_m \qquad \forall m, \forall t \tag{8}$$

$$ePGU_{m,t,\omega} \le (Fpgu_{m,t,\omega} - Xpgu_{m,t,\omega}.\beta_{pgu}) / \alpha_{pgu} \qquad \forall m, \forall t, \forall \omega \tag{9}$$

Thermal energy generated from both the PGU and boiler units can be transmitted to the thermal storage or heating and cooling components while satisfying the following constraint:

$$tECCS_{m,t} + tECc_{m,t} + tEHc_{m,t} \le \eta_{pgu}.Fpgu_{m,t,\omega} + \eta_{bo}.Fbo_{m,t} \qquad \forall m, \forall t, \forall \omega \tag{10}$$

The limitation of electricity generated by PV panels is formulated as follows:

$$ePV_{m,t,\omega} \le Spv_m.\eta_{PV}.SOL_t \qquad \forall m, \forall t, \forall \omega \tag{11}$$

Discharging and charging of a battery storage unit cannot occur at the same time. Thus,

$$XBd_{m,t,\omega} + XBc_{m,t,\omega} \le 1 \qquad \forall m, \forall t, \forall \omega \tag{12}$$

The electricity stored in a battery should be within its acceptable range as denoted in (13), which depends on the charging and discharging activities indicated in (14) and (15).

$$SBS_m.\gamma_{B\min} \le eB_{m,t,\omega} \le SBS_m \qquad \forall m\ ,\ \forall t\ ,\ \forall \omega \tag{13}$$

$$eB_{m,t,\omega} = IeB + (eBc_{m,t,\omega} - eBd_{m,t,\omega}).\Delta t \qquad \forall m\ ,\ t=1\ ,\ \forall \omega \tag{14}$$

$$eB_{m,t,\omega} - eB_{m,t-1,\omega} = (eBc_{m,t,\omega} - eBd_{m,t,\omega}).\Delta t \qquad \forall m\ ,\ \forall t \ge 2\ ,\ \forall \omega \tag{15}$$

The amount of discharging and charging should not exceed the allowable range, i.e.,

$$\gamma_{Bc\min}.SBS_m.XBc_{m,t,\omega} \le eBc_{m,t,\omega} \le \gamma_{Bc\max}.SBS_m.XBc_{m,t,\omega} \qquad \forall m\ ,\ \forall t\ ,\ \forall \omega \tag{16}$$

$$\gamma_{Bd\min}.SBS_m.XBd_{m,t,\omega} \le eBd_{m,t,\omega} \le \gamma_{Bd\max}.SBS_m.XBd_{m,t,\omega} \qquad \forall m\ ,\ \forall t\ ,\ \forall \omega \tag{17}$$

Similar to battery storage, discharging and charging of thermal storage units cannot occur at the same time. Hence,

$$XtSc_{m,t} + XtSd_{m,t} \le 1 \qquad \forall m\ ,\ \forall t \tag{18}$$

Thermal energy stored in thermal storage units should be within its acceptable range as denoted in (19), which depends on the charging and discharging activities expressed in (20) and (21).

$$STS_m.\gamma_{Ts\min} \le tES_{m,t} \le STS_m \qquad \forall m\ ,\ \forall t \tag{19}$$

$$tES_{m,t} = ItS + (tSc_{m,t} - tSd_{m,t}).\Delta t \qquad \forall m\ ,\ t=1 \tag{20}$$

$$tES_{m,t} - tES_{m,t-1} = (tSc_{m,t} - tSd_{m,t}).\Delta t \quad \forall m\ ,\ \forall t \ge 2 \tag{21}$$

Thermal storage energy must be smaller than its maximum capacity as per (22), and the available energy for charging the thermal storage is also considered as a charging rate constraint in (23).

$$tECCS_{m,t} + tEcS_{m.t} + tEhS_{m.t} \le STS_m \qquad \forall m\ ,\ \forall t \tag{22}$$

$$tESCc_{m,t} + tESHc_{m,t} \le tSd_{m,t}.\eta_{tSd} \qquad \forall m\ ,\ \forall t \tag{23}$$

Discharging rate is taken into account in the determination of energy supply by the thermal storage in (24).

$$tSc_{m,t} \le (tECCS_{m,t} + tEcS_{m.t} + tEhS_{m.t}).\eta_{tSc} \quad \forall m\ ,\ \forall t \tag{24}$$

Moreover, the amount of thermal energy discharging and charging should not exceed the allowable ranges according to (25)–(26).

$$\gamma_{Tsc\min}.STS_m.XtSc_{m,t} \le tSc_{m,t} \le \gamma_{Tsc\max}.STS_m.XtSc_{m,t} \quad \forall m\ ,\ \forall t \tag{25}$$

$$\gamma_{Tsd\min}.STS_m.XtSd_{m,t} \le tSd_{m,t} \le \gamma_{Tsd\max}.STS_m.XtSd_{m,t} \quad \forall m\ ,\ \forall t \tag{26}$$

Energy cannot be imported and exported at the same time between microgrids and LTM. This is reflected in the following constraints:

$$XEin_{m,t} + XEout_{m,t} \le 1 \quad \forall m\ ,\ \forall t \tag{27}$$

$$XCin_{m,t} + XCout_{m,t} \le 1 \quad \forall m\ ,\ \forall t \tag{28}$$

$$XHin_{m,t} + XHout_{m,t} \le 1 \quad \forall m\ ,\ \forall t \tag{29}$$

The energy transaction between a microgrid and the LTM depends on each energy transaction state, which is illustrated by the following equations:

$$eLtM_{m,t,\omega} \le M.XEin_{m,t} \quad \forall m\ ,\ \forall t\ ,\ \forall \omega \tag{30}$$

$$eMtL_{m,t,\omega} \le M.XEout_{m,t} \quad \forall m\ ,\ \forall t\ ,\ \forall \omega \tag{31}$$

$$CLtM_{m,t} \le M.XCin_{m,t} \quad \forall m\ ,\ \forall t \tag{32}$$

$$CMtL_{m,t} \le M.XCout_{m,t} \quad \forall m\ ,\ \forall t \tag{33}$$

$$HLtM_{m,t} \le M.XHin_{m,t} \quad \forall m\ ,\ \forall t \tag{34}$$

$$HMtL_{m,t} \le M.XHout_{m,t} \quad \forall m\ ,\ \forall t \tag{35}$$

where M is an upper limit.

Equations (36) – (38) are applied to establish an energy balance between supply and demand in the LTM.

$$\sum_m eLtM_{m,t,\omega} = \sum_m eMtL_{m,t,\omega} \quad \forall t\ ,\ \forall \omega \tag{36}$$

$$\sum_m CLtM_{m,t} = \sum_m CMtL_{m,t} \quad \forall t \tag{37}$$

$$\sum_{m} HLtM_{m,t} = \sum_{m} HMtL_{m,t} \qquad \forall t \tag{38}$$

In order to make the proposed structure safely for implementing in the practical cases, the network constraints of the networked microgrids are considered. For this aim, energy transactions between all microgrids with each other and power grid should be limited in the allowable range according to the following constraints.

$$eLtM_{m,t,\omega}, eMtL_{m,t,\omega} \le eL^{Max} \qquad \forall m\ ,\ \forall t,\ \forall \omega \tag{39}$$

$$CLtM_{m,t}, CMtL_{m,t} \le cL^{Max} \qquad \forall m\ ,\ \forall t \tag{40}$$

$$HLtM_{m,t}, HMtL_{m,t} \le hL^{Max} \qquad \forall m\ ,\ \forall t \tag{41}$$

$$eNtM_{m,t,\omega}, eMtN_{m,t,\omega} \le eM^{Max} \quad \forall m\ ,\ \forall t,\ \forall \omega \tag{42}$$

The maximum electrical energy trading among microgrids and with the main grid is assumed as 3 MW in this study.

The constraints (27) to (42) keep the energy trading among microgrids in allowable ranges with the aim of making the proposed framework applicable in the practical cases. Indeed, the mentioned constraints should be satisfied to keep the bus voltages and line currents in permissible ranges.

In the LTM, microgrids do not share energy with each other directly but inject a surplus of energy to the LTM when their energy production level is greater than energy consumption and take the same energy amount out when is needed considering the minimum energy costs.

4. Operation models for transactive energy management

In this paper, four operation decision models are considered for the evaluation of transactive energy effects on the energy exchange among the microgrids and power grid. The differences between the proposed models are briefly indicated in Table 1 in terms of individual and collective interests of the microgrids in the cluster.

Table 1. Differences between the features of the proposed models for microgrids.

Microgrid benefits	**Index of proposed models**			
	I	**II**	**III**	**IV**
Individual interests	✓	✗	✓	✓
Collective interests	✗	✓	✓	✓

Collective and a satisfactory level of individual interests	✗	✗	✓	✓
Collective and individual interests with same percentage of cost saving	✗	✗	✗	✓

This research is structured from the microgrids operator's viewpoint that seeks to maximize microgrids' benefits. Indeed, the objective function of this research is a cost-based single objective that is formulated to minimize microgrids' energy cost based on the proposed operational models. For each model, the CCP method is applied to come up with optimal decisions for the realization of random data. In this method, some constraints are allowed to be violated with a certain probability. We consider the production of PV and selling and purchasing prices as uncertainty parameters and let them be random variables in the CCP method. Therefore, all constraints that include the abovementioned parameters can violate with probability 10% in the CCP. Indeed, we assume $\varphi = 90\%$ for this study. One of the important goals of this work is proposing the free energy trading possibility for the microgrids in the cluster. It is assumed that all microgrids have agreed to participate in the cluster not only to gain the individual and collective benefits but also to help the dynamic energy balancing in the cluster. Therefore, the energy trading price between all microgrids with each other is zero (free) in this free energy trading environment. All of the proposed models are solved considering the free energy trading condition in the LTM, which is called Case I throughout this paper. To ensure the stability of the transactive energy technology in the energy management of the microgrids, the complete constraints are applied for all components especially energy trading in the LTM and power grid. All these constraints are employed for providing safely structure for the power grid that lets reliable energy sharing among microgrids and with the main grid by setting realistic parameters based on the information of microgrids in the Chicago area.

In addition, to evaluate the implications of considering the cost of energy exchanging between microgrids on their total cost and cost-saving, model II as the sample studied model is assumed in two modes of operation; case I indicates freely trade of energy among microgrids and case II is considered to model the LTM with costs of electrical and thermal energy exchange among the microgrids. Due to this, EPL_t, CPL_t, and HPL_t are assumed as the prices for electricity, cooling, and heating energy of the LTM, respectively. The amount of these prices are listed in Table 2. Furthermore, the objective function in case I is calculated using (3) but in case II, the following equation is employed where E_m is added as another term to (3):

$$E_m = \sum_{\omega}\sum_{t} EPL_t.(eLtM_{m,t,\omega} - eMtL_{m,t,\omega}) + \sum_{t} CPL_t.(CLtM_{m,t} - CMtL_{m,t})$$
$$+\sum_{t} HPL_t.(HLtM_{m,t} - HMtL_{m,t}) \qquad \forall m \tag{43}$$

In (43), the positive amount of E_m would be revenue from energy transactions for microgrid *m* while it would be energy cost when the positive value is reached for E_m in the energy trading market.

4.1. Model I

Model I is considered for evaluation of energy trade between the microgrids and the power grid in individual mode. The microgrids in this model cannot exchange energy with each other but with the power grid. The problem formulations of this model based on the CCP technique becomes:

$$\min\ \mathrm{F}_I = \sum_{m} F_{I,m} \tag{44}$$

subject to the constraints in (4) – (42).

$$XEin_{m,t} = 0,\ XEout_{m,t} = 0,\ XCin_{m,t} = 0,\ XCout_{m,t} = 0\ \forall m\ ,\forall t$$
$$XHin_{m,t} = 0\ ,\ XHout_{m,t} = 0 \qquad \forall m\ ,\ \forall t$$

where, $F_{I,m}$ is the energy cost for the m^{th} microgrid in model I, which is calculated using (3).

4.2. Model II

In this model, all microgrids could trade energy among themselves and with the power grid to maximize collective interests. Indeed, all microgrids exchange energy in order to minimize the total cost of the cluster. The mathematical equation of this model is as follows:

$$\min\ \mathrm{F}_{II} = \sum_{m} (F_{II,m} + E_m) \tag{45}$$

subject to the constraints in (4) – (42).

Table 2. Amount of energy trading prices among the microgrids.

Price ($/kW)	EPL_t	CPL_t	HPL_t
Amount	$pMtN_{t,\omega} + \left(pNtM_{t,\omega} - pMtN_{t,\omega}\right)/4$	0.01	0.01

where, $F_{II,m}$ is the energy cost for the m^{th} microgrid in model II, which is calculated using (3) and E_m=0 for case I.

4.3. Model III

Although maximum collective interests can be achieved by model II, individual interests may not be guaranteed under this model for each microgrid. In other words, some microgrids may not benefit when they join the cluster.

Therefore, model III is proposed not only to maximize collective interests but also to provide a satisfactory level of individual interests through extending model I with a set of constraints. In this model, the realization of the satisfactory level of individual interests is analyzed with the assumption of four various amounts of θ. Therefore, θ=0, 0.05, 0.1, and 0.14 are assumed for the assessment of Model III. Indeed, there is no logical producer in selecting the values of θ for example 0.14 instead of 0.15 and all of the selected magnitudes only are assumption amounts that are used with the aim of indicating the features of Model III. The equations in model III are modified as

$$\min \ \mathrm{F}_{III} = \sum_{m} F_{III,m} \tag{46}$$

Subject to:

$$p(F_{III,m} \leq F_{I,m}.(1-\theta)) \geq \varphi \qquad \forall m \tag{47}$$

Constraints (4) – (42).

where, $F_{III,m}$ is the energy cost for the m^{th} microgrid in model III, which is calculated using (3).

4.4. Model IV

Because the two previous models are not able to maximize both the collective and individual interests simultaneously, model IV is implemented to do so by considering the same percentages of the cost-saving for all microgrids. In this regard, variable μ is introduced as a percentage of cost-saving of microgrids for maximizing the relative individual interests in each microgrid.

$$\max \mu \tag{48}$$

Subject to:

$$p(F_{IV,m} \leq F_{I,m}.(1-\mu)) \geq \varphi \qquad \forall m \tag{49}$$

Constraints in (4) – (42).

where, $F_{IV,m}$ is the energy cost for the m^{th} microgrid in model IV, which is calculated using (3).

To sum up, the summary of the proposed models is completely shown in Fig. 3 to simply describe the features of the models.

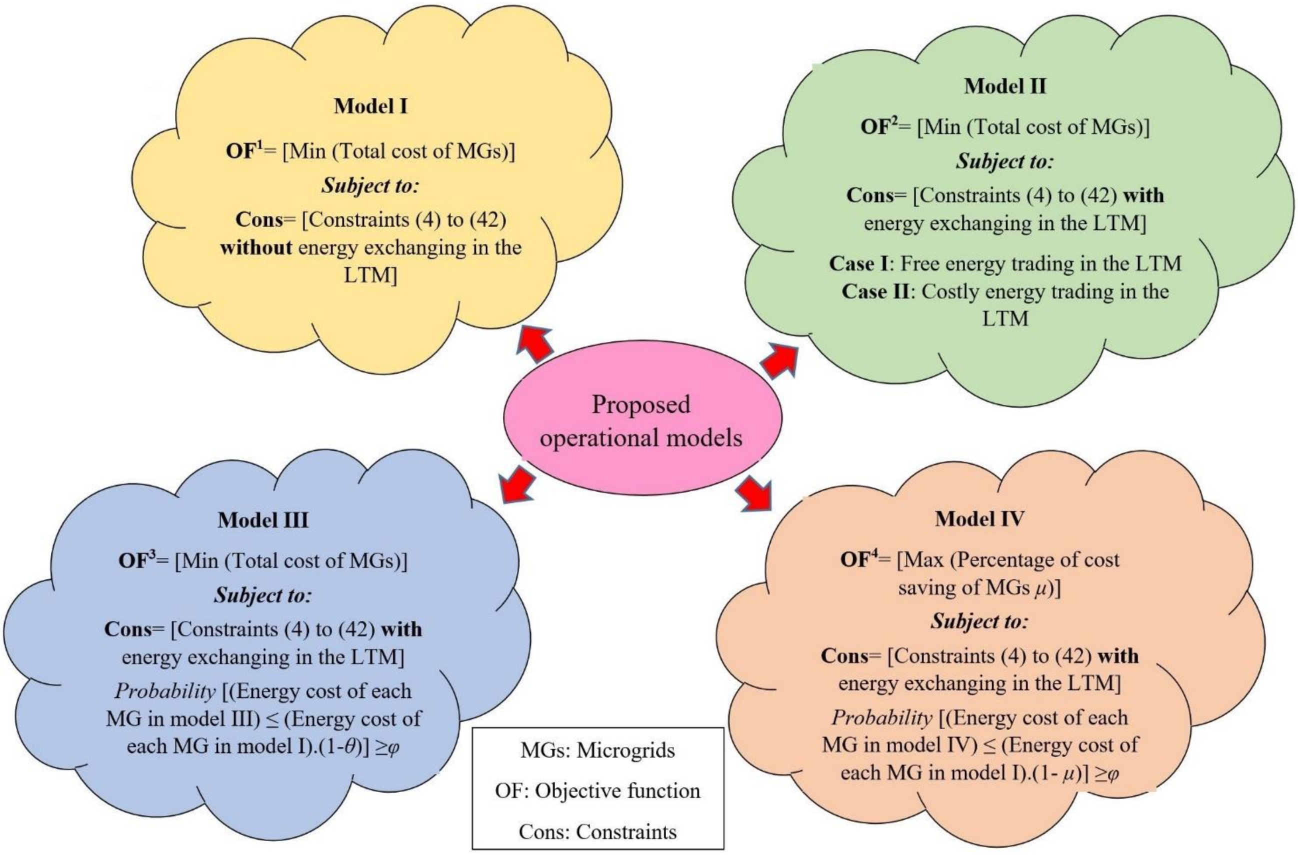

Fig. 3. Summary of the features of the proposed operational models

5. Simulation results

In this study, we utilized the CCP for the evaluation of energy trade between the power grid and sixteen commercial building level microgrids located in Chicago, U.S. The size of generation units in microgrids are different with each other and are considered based on their energy demand. Thus, the amount of cost-saving for microgrids will be different in the proposed models. All electrical and thermal loads for the Chicago area can be accessed in (Chen and Hu, 2016). The study is accomplished for the month of July. The time of use rate is used for purchasing and selling electricity (Daneshvar et al., 2018b). The information of the one-month data of solar radiation can be found in (Daneshvar et al., 2019). The size of the different devices is tabulated in Table 3 for all microgrids. Moreover, Table 4 includes the efficiency of all devices in the microgrids.

Table 3. The size of the different devices (in kW) in the microgrids.

Devices	**Microgrid index**							
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**

PV panel	255	830	1930	2417	1159	1045	3435	4898
PGU	20	194	2132	113	98	90	282	732
Boiler	63	581	5937	607	524	502	1459	6455
Battery storage	20	194	2132	113	98	90	282	732
Thermal storage	63	581	5937	607	524	502	1459	6455
Devices	**M9**	**M10**	**M11**	**M12**	**M13**	**M14**	**M15**	**M16**
PV panel	2090	116	255	2242	634	501	945	391
PGU	495	43	69	1574	370	139	498	63
Boiler	1174	170	302	2505	599	252	1114	271
Battery storage	495	43	69	1574	370	139	498	63
Thermal storage	1174	170	302	2505	599	252	1114	271

Table 4. The efficiency of the different devices in the microgrids.

Efficiency				
PV panel	**Heating component**	**Cooling component**	**PGU**	**Boiler**
0.22	0.85	0.7	0.51	0.9
Charging of battery storage	**Discharging of battery storage**	**Charging of thermal storage**	**Discharging of thermal storage**	
0.9	0.9	0.95	0.95	

All other parameters required for this research are the same as those considered in (Chen and Hu, 2016). We consider the uncertainties to be the electricity purchasing and selling prices, and the electricity production of PV panels. In addition, the LHS and fast forward reduction methods are used for scenario generation and reduction processes, respectively. Various scenarios are generated and then reduced for each of the uncertainty parameters. Furthermore, normal and beta distributions are employed for two price parameters and the electricity generation parameter by the PVs, respectively. Then, the inverse cumulative distribution functions (iCDF) are calculated. Eventually, the expected value of microgrid energy costs is computed for all proposed models. The problem presented in this paper is the MIP problem and GAMS software with a CPLEX solver is effectively used for solving it, which optimal solutions are reached from solving this problem. Indeed, the optimality of the extracted results is guaranteed due to the use of the CPLEX solver for the MIP problem without any nonlinear equations. Numerical results of all studied models are tabulated in Table 5. The number of variables and constraints, as well as the computing time of the problem for each of the four models, are tabulated in Table 6 and simulations of them were completed by a PC with Intel Core i7-6700HQ CPU @ 2.60 GHz with 16.00 GB RAM.

Table 5. Numerical results of all evaluated models in Case I.

MI	Model I	Model II	Model III				Model IV
			θ=0	θ=0.05	θ=0.1	θ=0.14	
M1	62.131	60.994	62.131	59.024	55.918	53.433	52.190
M2	1142.442	1875.891	980.728	1085.320	1028.198	982.500	959.651
M3	19469.523	18631.331	19469.523	18496.047	17522.571	16575.108	16354.399
M4	-180.324	-540.972	-180.324	-189.340	-198.356	-205.569	-208.800
M5	393.664	1102.838	393.664	373.981	354.298	338.551	330.678
M6	372.428	904.905	372.428	353.807	335.185	320.288	312.840
M7	734.255	2354.395	734.255	697.542	660.830	631.459	616.774
M8	11448.603	6530.355	9738.987	9973.248	10303.743	8271.058	9616.827
M9	2055.836	3697.557	2055.836	1953.044	1850.252	1768.019	1726.902
M10	430.989	643.484	347.056	296.335	231.657	370.651	362.031
M11	612.164	786.233	444.101	581.556	542.120	526.461	514.218
M12	30246.964	16757.205	17816.650	19150.840	20221.956	22087.069	25407.450
M13	4587.275	2921.001	3641.549	3302.571	3216.704	3945.056	3853.311
M14	1303.752	1289.085	926.439	1003.741	1077.995	1121.227	1095.152
M15	6318.359	4991.470	5321.398	5040.477	4979.537	5433.789	5307.422
M16	597.300	731.861	596.750	564.576	537.570	513.678	501.732
Total Cost	79595.361	62737.635	62721.171	62742.768	62720.178	62732.778	66802.775

Table 6. Number of variables and constraints along with the computing time of the problem.

Specifications	Model I	Model II	Model III				Model IV
			θ=0	θ=0.05	θ=0.1	θ=0.14	
Variables	36	36	36	36	36	36	37

Constraints	24	39	40	40	40	40	40
Run time (s)	2.84	4.65	4.88	5.42	7.15	8.34	14.61

The results provided in this table indicate that model II can provide collective interests for the microgrids in both cases I and II while reducing the total energy costs in comparison with model I. The energy cost in case I is less than that of case II, which means that if microgrids exchange energy freely with each other (case I), they can achieve the lowest cost. All microgrids' cost savings of this model are illustrated in Fig. 4. For the case I in model II, microgrids 4 and 7 have the maximum and minimum percentage of cost-saving, respectively. The behavior of the above microgrids (4 and 7) in receiving total electrical energy from all sectors is demonstrated in Fig. 5 for 1st of July as a sample day.

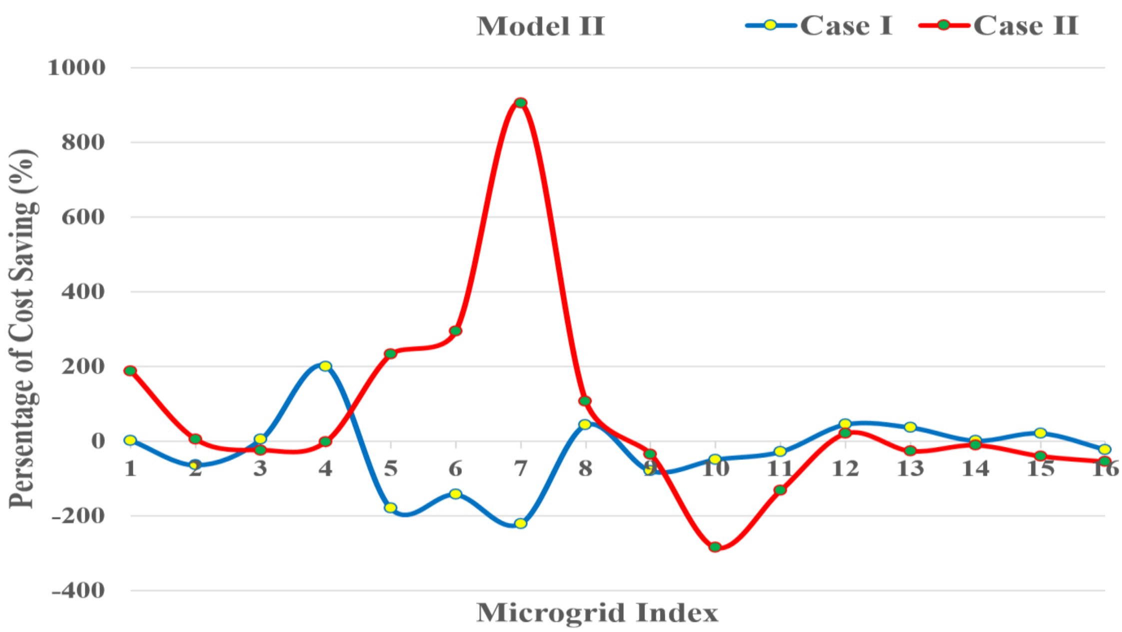

Fig. 4. Percentages of energy cost saving for all microgrids in model II

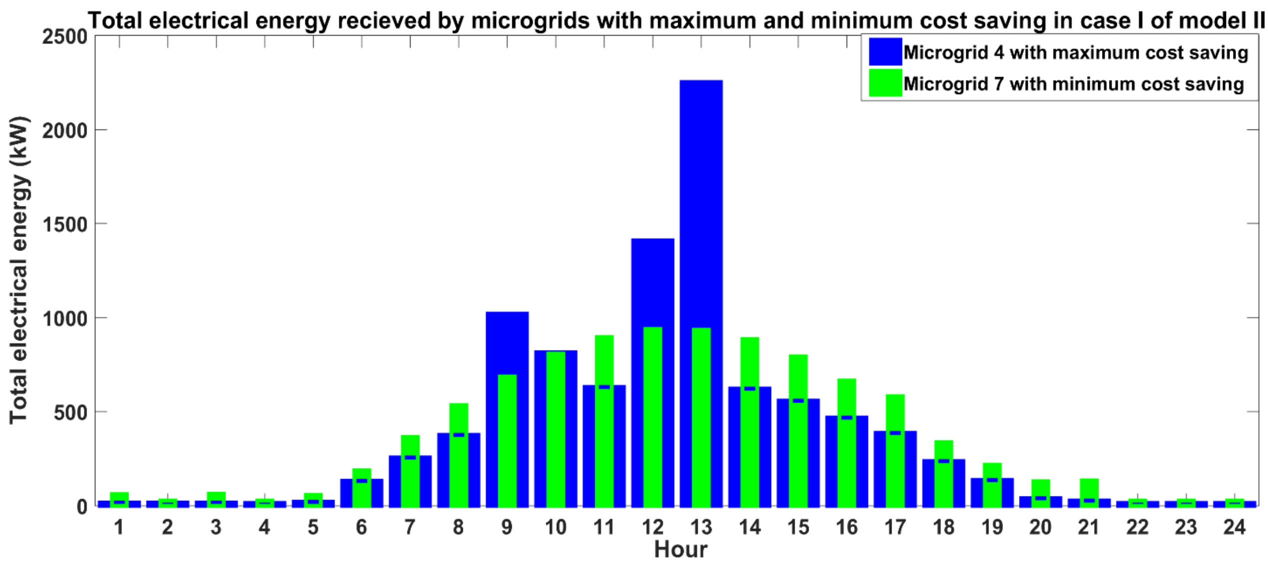

Fig. 5. Behavior of microgrids 4 and 7 in receiving total electrical energy

In Fig. 5, both microgrids 4 and 7 have received more energy in the time intervals 12 to 14 when electrical energy consumption is at its peak level. However, some microgrids have a negative cost-saving and they are losing money when they joined the cluster in this model.

Therefore, model III is considered not only to provide collective interests but also to establish acceptable levels of individual interests for microgrids. This model is implemented in different assumed amounts of expected percentages of cost-saving that are depicted in Fig. 6. For this reason, when $\theta = 0.14$ the microgrids have nearly cost-saving and better condition compared to other modes. However, none of the mentioned cost savings is the optimal solution for the microgrids percentage of cost-saving and they are only assumptive values. Moreover, the amount of cost saving in the microgrids varies denoting that some microgrids have larger cost savings in comparison with others. The mentioned drawbacks of model III made us proud to propose a new model that can provide the same percentage of cost-saving for all microgrids.

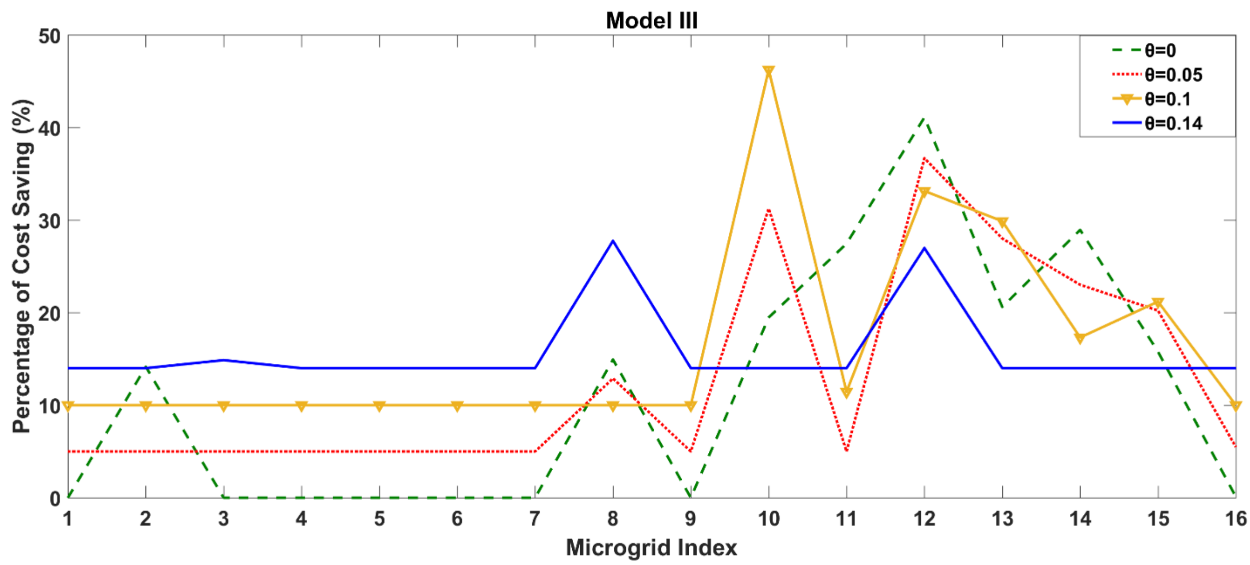

Fig. 6. Percentages of cost-saving for all microgrids in model III

Therefore, in order to satisfy the relative amount of cost-saving of the microgrids, model IV is proposed to provide the same percentage of cost-saving. After running this model, 16% cost saving was obtained for all microgrids. In this model, each of the microgrids can gain the percentage of cost-saving depending on their size in the system. However, 16% saving for microgrids will imply different values to the operators. For example, for the microgrids 1 and 13, the mentioned percentage of cost-saving imposes $9.941 and $733.964 cost-saving, respectively. In this work, microgrid 12 with a suitable amount of cost-saving and is assumed as a sample microgrid and 1st of July is considered as a sample day for evaluation of electrical energy exchange between various components of the system. For this purpose, the portion of each electrical energy resource in meeting the demand of microgrid 12 is shown in Fig. 7.

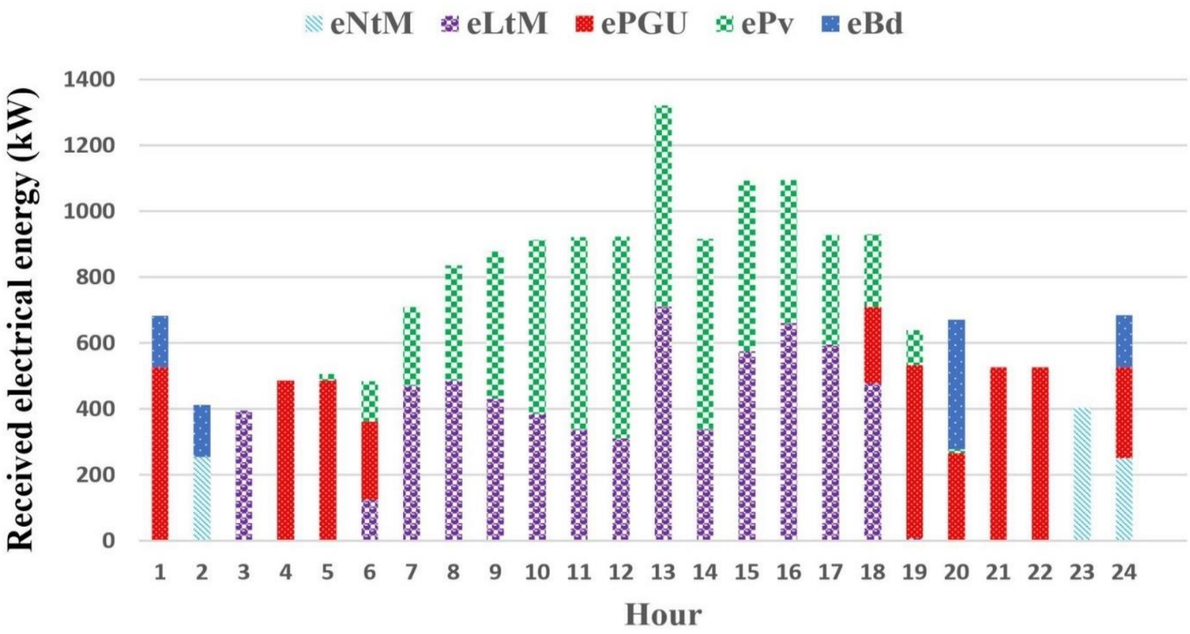

Fig. 7. Electrical energy coming to the microgrid 12 on 1st of July

From this figure, renewable energy and shared energy are used for meeting the demand in the microgrid with minimum energy costs and dependency on the power grid. To sum up, after the analyzing of the proposed models in providing the collective and individual interests along with the energy management and control for the microgrids based on the transactive energy technology, model IV not only can provide mentioned benefits for the microgrids but also achieving the same percentage of cost saving can also be realized based on this model. Therefore, model IV as the complete transactive energy-based model is proposed for all microgrids in the system to exchange energy with each other and the power grid based on the reliable technology paradigm. As mentioned in the previous sections, all microgrids can trade electrical and thermal energy with each other within the LTM structure. The amount of electrical, heating, and cooling energy transmitted (received) to (by) the LTM by (from) all microgrids is illustrated in Fig. 8 for a given day in July as an illustrative example. As obvious from this figure, all microgrids have a large amount of electrical energy exchanging with LTM during the morning hours (8-10 am), noon (11-12 am and 12-1 pm), and evening (1-5 pm) when the amount of electricity demand is higher than other times. Moreover, the amount of cooling energy consumption is increased as the sun rises and the maximum cooling demand is reached at noon when the temperature is high due to the maximum solar radiation, which in turn necessitates more cooling energy trading of microgrids in the mentioned times. On the other hand, the amount of heating energy exchange among microgrids peaks in the early morning (4-9 am) and during the night (9-11 pm) when the heating demand is relatively higher.

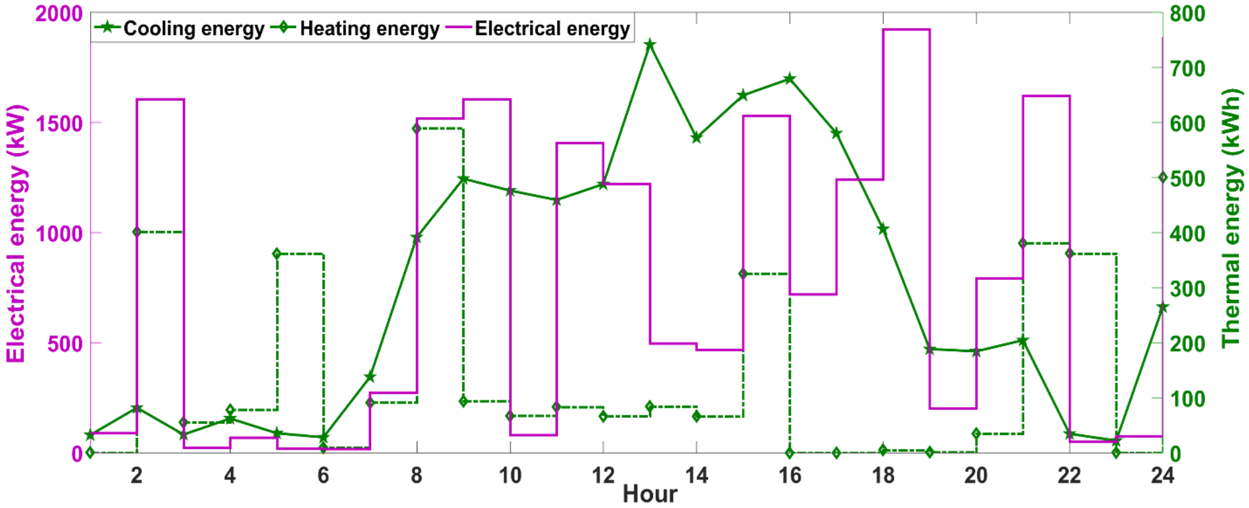

Fig. 8. Electrical and thermal energy traded between all microgrids in the LTM for a sample day

6. Conclusion

This paper proposed four models to scrutinize the energy exchange between sixteen microgrids and the power grid using the notion of transactive energy as a sustainable approach. In this research, the chance-constrained programming method was utilized to solve the problem while considering realistic conditions for field data obtained from the Chicago area. Four types of models were developed and analyzed in this study. Model I assumed that the microgrids do not have any energy sharing among themselves. Maximizing collective interests was considered in model II when the microgrids could exchange energy with each other. Model III was structured to provide an admissible level of cost-saving for each microgrid along with meeting collective interests. Finally, the last model was structured for satisfying the collective interest as well as relative individual interests. The numerical results indicated that although the minimum total energy cost ($62720,178) is reached in model III, this model could not provide a suitable amount of cost-saving for all microgrids meaning that individual benefit of some microgrids could be ignored in this model. However, model IV could provide the same amount of cost-saving (better individual benefits) for microgrids in comparison with other models while preserving the collective interest of microgrids. Hence, the microgrids were able to achieve both the individual and collective benefits in model IV, when they joined the cluster and operated under the transactive energy scheme. Indeed, using the transactive energy technology in developing the LTM has led to providing an appropriate energy trading mechanism for the interconnected microgrids. Based on this mechanism, all microgrids could gain both the collective and individual benefits in the cluster mode.

Although considering both the collective and individual interests of the microgrids is an important issue in the cluster mode, proposing the effective models that can meet both the mentioned interests for them in the systems with a high level of the stochastic producers is also a significant issue that needs to be intended. Indeed, equipping the microgrid to the high level of RERs for more clean energy production is necessary due to the economic and environmental issues. In such a condition, all microgrids will need the capable models that not only can meet both the collective and individual interests for them but also can provide robust conditions with the aim of guaranteeing the reach of the special amount of cost-saving for each of the microgrids. Moreover, considering this issue that which microgrids have injected energy into the LTM at a particular time and which ones receive the energy from LTM will also be an important point in exactly dividing the profits between the microgrids in the cluster, which all of these topics can be intended as the future trends for this work.

References

Bazmohammadi, N., Tahsiri, A., Anvari-Moghaddam, A., Guerrero, J.M., 2019a. A hierarchical energy management strategy for interconnected microgrids considering uncertainty. International Journal of Electrical Power & Energy Systems 109, 597-608.

Bazmohammadi, N., Tahsiri, A., Anvari-Moghaddam, A., Guerrero, J.M., 2019b. Stochastic Predictive Control of Multi-Microgrid Systems. IEEE Transactions on Industry Applications.

Chen, Y., Hu, M., 2016. Balancing collective and individual interests in transactive energy management of interconnected micro-grid clusters. Energy 109, 1075-1085.

Chen, Y., Wen, J., Cheng, S., 2012. Probabilistic load flow method based on Nataf transformation and Latin hypercube sampling. IEEE Transactions on Sustainable Energy 4(2), 294-301.

Chen, Z., Yuan, Y., Zhang, S.-S., Chen, Y., Yang, F.-L., 2013. Management of occupational exposure to engineered nanoparticles through a chance-constrained nonlinear programming approach. International Journal of Environmental Research and Public Health 10(4), 1231-1249.

Daneshvar, M., Ivatloo, B.M., Abapour, M., Asadi, S., Khanjani, R., 2020. Distributionally Robust Chance Constrained Transactive Energy Framework for Coupled Electrical and Gas Microgrids. IEEE Transactions on Industrial Electronics, 1-1.

Daneshvar, M., Mohammadi-Ivatloo, B., Anvari-Moghaddam, A., 2019. Optimal Energy Trading Strategy for Proactive DISCO considering Demand Response Programs in the distribution networks, CIGRE Symposium 2019. CIGRE (International Council on Large Electric Systems), pp. 1-10.

Daneshvar, M., Mohammadi-ivatloo, B., Zare, K., 2018a. Integration of Distributed Energy Resources Under the Transactive Energy Structure in the Future Smart Distribution Networks, Operation of Distributed Energy Resources in Smart Distribution Networks. Elsevier, pp. 349-379.

Daneshvar, M., Pesaran, M., Mohammadi-ivatloo, B., 2018b. Transactive energy integration in future smart rural network electrification. Journal of Cleaner Production 190, 645-654.

Dehghani-Pilehvarani, A., Markou, A., Ferrarini, L., 2019. A hierarchical distributed predictive control approach for microgrids energy management. Sustainable Cities and Society 48, 101536.

Dehghanpour, K., Nehrir, H., 2017. An agent-based hierarchical bargaining framework for power management of multiple cooperative microgrids. IEEE Transactions on Smart Grid 10(1), 514-522.

Dolatabadi, A., Mohammadi-Ivatloo, B., 2017. Stochastic risk-constrained scheduling of smart energy hub in the presence of wind power and demand response. Applied Thermal Engineering 123, 40-49.

Fioriti, D., Poli, D., 2019. A novel stochastic method to dispatch microgrids using Monte Carlo scenarios. Electric Power Systems Research 175, 105896.

Frick, D., Sessa, P.G., Wood, T.A., Kamgarpour, M., 2019. Exploiting structure of chance constrained programs via submodularity. Automatica 105, 89-95.

Hajian, M., Glavic, M., Rosehart, W.D., Zareipour, H., 2012. A chance-constrained optimization approach for control of transmission voltages. IEEE Transactions on Power Systems 27(3), 1568-1576.

He, M., Giesselmann, M., 2015. Reliability-constrained self-organization and energy management towards a resilient microgrid cluster, 2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT). IEEE, pp. 1-5.

Huang, Y., Huang, G., Liu, D., Zhu, H., Sun, W., 2012. Simulation-based inexact chance-constrained nonlinear programming for eutrophication management in the Xiangxi Bay of Three Gorges Reservoir. Journal of Environmental Management 108, 54-65.

Justo, J.J., Mwasilu, F., Lee, J., Jung, J.-W., 2013. AC-microgrids versus DC-microgrids with distributed energy resources: A review. Renewable and Sustainable Energy Reviews 24, 387-405.

Kanchev, H., Lu, D., Colas, F., Lazarov, V., Francois, B., 2011. Energy management and operational planning of a microgrid with a PV-based active generator for smart grid applications. IEEE Transactions on Industrial Electronics 58(10), 4583-4592.

Keyvanloo, M., Kimiagari, A., Esfahanipour, A., 2015. A hybrid approach to select the best sourcing policy using stochastic programming. Journal of Manufacturing Systems 36, 115-127.

Lu, T., Wang, Z., Ai, Q., Lee, W.-J., 2017. Interactive model for energy management of clustered microgrids. IEEE Transactions on Industry Applications 53(3), 1739-1750.

Marino, C., Quddus, M.A., Marufuzzaman, M., Cowan, M., Bednar, A.E., 2018. A chance-constrained two-stage stochastic programming model for reliable microgrid operations under power demand uncertainty. Sustainable Energy, Grids and Networks 13, 66-77.

Marvasti, A.K., Fu, Y., DorMohammadi, S., Rais-Rohani, M., 2014. Optimal operation of active distribution grids: A system of systems framework. IEEE Transactions on Smart Grid 5(3), 1228-1237.

Mehrjerdi, H., Rakhshani, E., 2019. Optimal operation of hybrid electrical and thermal energy storage systems under uncertain loading condition. Applied Thermal Engineering 160, 114094.

Merabet, A., Ahmed, K.T., Ibrahim, H., Beguenane, R., Ghias, A.M., 2016. Energy management and control system for laboratory scale microgrid based wind-PV-battery. IEEE Transactions on Sustainable Energy 8(1), 145-154.

Moayedi, S., Davoudi, A., 2015. Distributed tertiary control of DC microgrid clusters. IEEE Transactions on Power Electronics 31(2), 1717-1733.

Mühlpfordt, T., Faulwasser, T., Hagenmeyer, V., 2018. A generalized framework for chance-constrained optimal power flow. Sustainable Energy, Grids and Networks 16, 231-242.

Nunna, H.K., Srinivasan, D., 2017. Multiagent-based transactive energy framework for distribution systems with smart microgrids. IEEE Transactions on Industrial Informatics 13(5), 2241-2250.

Nunna, K.H., Doolla, S., 2014. Responsive end-user-based demand side management in multimicrogrid environment. IEEE Transactions on Industrial Informatics 10(2), 1262-1272.

Prathapaneni, D.R., Detroja, K.P., 2019. An integrated framework for optimal planning and operation schedule of microgrid under uncertainty. Sustainable Energy, Grids and Networks 19, 100232.

Prinsloo, G., Dobson, R., Mammoli, A., 2018. Synthesis of an intelligent rural village microgrid control strategy based on smartgrid multi-agent modelling and transactive energy management principles. Energy 147, 263-278.

Rahimi, F., Ipakchi, A., Fletcher, F., 2016. The changing electrical landscape: end-to-end power system operation under the transactive energy paradigm. IEEE Power and Energy Magazine 14(3), 52-62.
Schwarm, A.T., Nikolaou, M., 1999. Chance-constrained model predictive control. AIChE Journal 45(8), 1743-1752.
Sedighizadeh, M., Esmaili, M., Mohammadkhani, N., 2018. Stochastic multi-objective energy management in residential microgrids with combined cooling, heating, and power units considering battery energy storage systems and plug-in hybrid electric vehicles. Journal of Cleaner Production 195, 301-317.
Shezan, S.A., Julai, S., Kibria, M., Ullah, K., Saidur, R., Chong, W., Akikur, R., 2016. Performance analysis of an off-grid wind-PV (photovoltaic)-diesel-battery hybrid energy system feasible for remote areas. Journal of Cleaner Production 125, 121-132.
Utkarsh, K., Srinivasan, D., Trivedi, A., Zhang, W., Reindl, T., 2018. Distributed model-predictive real-time optimal operation of a network of smart microgrids. IEEE Transactions on Smart Grid 10(3), 2833-2845.
Wang, H., Huang, J., 2016. Cooperative planning of renewable generations for interconnected microgrids. IEEE Transactions on Smart Grid 7(5), 2486-2496.
Wang, S., Gangammanavar, H., Ekşioğlu, S.D., Mason, S.J., 2017. Stochastic optimization for energy management in power systems with multiple microgrids. IEEE Transactions on Smart Grid 10(1), 1068-1079.
Wang, Y., Mao, S., Nelms, R.M., 2015. On hierarchical power scheduling for the macrogrid and cooperative microgrids. IEEE Transactions on Industrial Informatics 11(6), 1574-1584.
Wu, L., Shahidehpour, M., Li, T., 2007. Stochastic security-constrained unit commitment. IEEE Transactions on Power Systems 22(2), 800-811.
Yousefi, H., Ghodusinejad, M.H., Kasaeian, A., 2017. Multi-objective optimal component sizing of a hybrid ICE+ PV/T driven CCHP microgrid. Applied Thermal Engineering 122, 126-138.
Yu, H., Chung, C., Wong, K., Lee, H., Zhang, J., 2009. Probabilistic load flow evaluation with hybrid latin hypercube sampling and cholesky decomposition. IEEE Transactions on Power Systems 24(2), 661-667.
Zhang, Y., Gatsis, N., Giannakis, G.B., 2013. Robust energy management for microgrids with high-penetration renewables. IEEE Transactions on Sustainable Energy 4(4), 944-953.
Zhao, T., Ding, Z., 2017. Distributed agent consensus-based optimal resource management for microgrids. IEEE Transactions on Sustainable Energy 9(1), 443-452.