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A Stochastic Operational Decision Framework For Multiple Local Energy Communities Considering Dependencies in Uncertainty

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***Abstract*—This paper presents a stochastic decision framework for multiple local energy communities (M-LECs) considering risk behaviour and dependencies in uncertainty. The proposed problem is presented in a bilevel stochastic framework comprising of M-LECs at the upper level and load-serving entity (LSE) at the lower level in the distribution system (DS). The M-LECs strategically optimizes their operating cost using a grid-informed price, distribution locational marginal price, cleared by LSE for peer-to-peer trading, and LECs to grid power transactions. Further, the uncertainty of various sources is modeled using a multi-variate copula distribution to consider their dependencies. The copula model generates correlated random samples to quantify the relationship among different uncertain variables. The problem is mathematically formulated using equilibrium problem with equilibrium constraints (EPEC). The simulation results are implemented on a modified IEEE-33 bus system to demonstrate the effectiveness of the proposed methodology.**

***Index Terms*—Multiple local energy communities, bi-level stochastic problem, peer-to-peer trading, copula, risk optimization.**

I. Introduction

LOCAL energy communities (LECs) are considered emerging innovation in the era of decentralization and distributed operation. It supports distributed generation, sustainable, socioeconomic development, flexibility, peer-to-peer (P2P) trading, community sharing, autonomy, etc., These LECs are typically embedded with various resources/loads such as distributed energy resources (DERs), flexible loads (FLs), energy storage systems (ESSs), etc [1]. However, supportive community engagement, resource uncertainty, operational feasibility and grid integration have also emerged as major challenges in LECs.

The research perspectives of LECs have been explored in the literature in various domains such as operations, management, economics, etc., [1], [2]. The early works on LECs were typically developed using deterministic approaches. It focuses on LECs' operation and optimization using optimal utilization of DERs, FLs, ESSs, and P2P trading [1]. Further, the interaction framework for LECs has been established using prosumers within [3] and with other entities such as distribution system operator (DSO) [4], and LECs/microgrids (MGs). These works focus on the benefits of LECs in terms of economic feasibility, profitability, energy sharing, P2P transaction. However, less attention has been paid to the impact of various uncertainty and variability sources on the LECs' operation and risk behavior [1]. Moreover, the operation of LECs has been analyzed using individual LEC's perspective [1], [5], [6].

The transition to renewable energy sources (RESs) has encouraged sustainable and green energy developments in LECs. However, RESs are also a source of intermittency and uncertainty, exposing grid operators and other generation sources to risk and volatility [7]–[9]. Uncertainty and intermittency in LECs have been investigated using various approaches and countermeasures in the literature [7], [9], [10]. Unified energy management using PV with flexible resources in MGs was applied in [7], transactive energy between MGs and DSO considering price, PV, loads, and electric vehicles uncertainty [9], and energy and regulation management with load and PV uncertainty [10]. In [11], a chance-constrained based P2P operation in energy and reserve market is formulated considering the RES uncertainty [11]. In [12], a P2P trading is described considering RES and load uncertainty. These aforementioned works have addressed uncertainty concerns using the stochastic optimization [1], robust optimization (RO) [8], adaptive RO [10], and distributionally RO [9]. However, with the exception of a handful of studies [9], [12], these works have lightly touched on the dependency in uncertainty [13], [14] and risk behavior [15] in the context of P2P trading in LEC.

Moreover, P2P pricing strategies, inclusion of grid network in P2P pricing, network usage charges (NUC), dependency in uncertainty, risk, and strategic operation of multiple LECs (M-LEC) [5], [6], all together are hardly addressed concerns in the LECs. Thus, this paper addresses these aforementioned concerns by considering a grid-informed, DLMP pricing inclusive of NUC for P2P, and grid transaction, dependency in uncertainty and risk behavior using the stochastic framework in M-LEC and is derived as the motivation of this study.

Based on this, the main contributions of paper are summarized as follows:

- A bilevel stochastic decision framework for the strategic operation of M-LECs is proposed considering uncertainty. The LEC at the upper level (UL) utilizes a temporal-spatial price, DLMP computed by LSE at the lower level (LL) for P2P and grid power transactions.
- A copula-based probabilistic model is proposed to capture the dependency in uncertainty for demand, price,

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PV and wind power. A correlated random sample of uncertain data is generated. Furthermore, the impact of uncertainty on the operation of M-LECs is considered through risk-based optimization using conditional value at risk (CVaR). The problem is implemented on a modified 33-bus distribution system.

II. Framework Formulation

A. Modeling of Multi-Variate Uncertainty Using Copulas

In multi-variate stochastic variables, the dependency among variables can be characterized using joint-stochastic methods. Joint-stochastic methods generate random variables with the correlation to capture their dependency. The multivariates establish a relationship to quantify their pattern behavior in uncertainty modeling. The copula theory is considered a convenient approach to model multi-variate distributions to capture their dependence structure [13], [14]. It is used to model the uncertainty of electricity demand, price, PV power, and wind power to consider their marginal and joint behavior in this paper.

Considering these stochastic variables, a d-dimensional random vector is formed over time horizon Ω_T and their joint cumulative distribution function (CDF) is F_X. From the Sklar's theorem, the relationship between joint CDF and copula distribution $C(.)$ can be uniquely expressed as follows [13]:

$$F_X(x_1, ..., x_d) = C(F_1(x_1), ..., F_d(x_d)) \tag{1}$$

where, $F_X(.)$ and $F_i := F(x_i)$ are joint CDF and marginal CDF, respectively. The Sklar's theorem provides an effective approach to describe individual marginal PDF for independent behavior and copula PDF for dependent behavior modeling. As, $F_1(x_1), ..., F_d(x_d)$ are a continuous and marginal CDF, then copula relationship can be equivalently written using the probability integral transform as follows:

$$C(u_1, ..., u_d) = F_X(F^{-1}(u_1), ..., F^{-1}(u_d)) \tag{2}$$

where, $u_1 = F_1(x_1)$ and $u_d = F_d(x_d)$ are uniform distributions. Similarly, the corresponding joint density function of the copula can be expressed as the product of marginal probability density function (PDF) f_i and copulas PDF $c(.)$ as follows:

$$f_X(x) = c(F_1(x_1), ..., F_d(x_d)) \prod_{i \in d} f_i(x_i) \tag{3}$$

The decoupling feature of copulas-based modeling makes it superior in multi-variate distribution. It has two different classes functions, namely, elliptical and Archimedean copulas. These classes have been categorized based on symmetry and asymmetry dependency structures. The sampling of random dependent variables for scenario generation and reduction is described in Algorithm 1.

Algorithm 1: Procedure of scenario generation sampling and reduction using copula

1) **Step 1.** Constructs the historical data matrix $X := (x_1, ..., x_d) = (P^l_{1,t}, \lambda_{2,t}, P^{pv}_{3,t}, P^{wt}_{d,t})$ for each time t for demand, price, solar and wind power.
2) **Step 2.** Transform the data matrix into a marginal CDF using Kernel Density Estimation (KDE) on uniform data [16].
3) **Step 3.** Fit the transformed marginal CDF data matrix to the copula function and estimate its parameters.
4) **Step 4.** Generate uniform random sample data using inverse transformation sampling using estimated parameters.
5) **Step 5.** Transform generated uniform random sample to actual scale using inverse probability transformation.
6) **Step 6.** Reduce the generated random variable using the scenario reduction method.

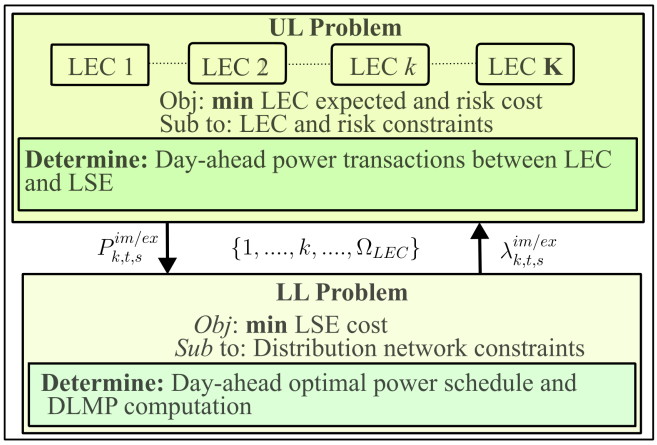


Fig. 1. Schematic Diagram of the proposed framework.

B. Bi-level Stochastic LEC Framework

This section presents a stochastic economic decision framework for M-LECs in day-ahead operation in DS. Fig. 1 shows the structure of bi-level problem, where M-LECs are competing with each other to optimize their operating costs at the UL and LSE optimizes its operating cost at the LL. The M-LECs interact with the grid for P2P and grid transactions using the temporal-spatial price, DLMP, cleared by LSE in day-ahead market operation.

1) Upper-Level Problem: LECs Cost: The objective of LEC is to optimize its expected total operating cost using the various resources and P2P trading with other LECs in the UL. It comprises of FLs, inflexible loads (IFLs), DERs, and ESSs. It is assumed that each LEC is operating over the different set of customer classes such as residential (R), large industrial (LI), medium industrial (MI) and commercial (C) to demonstrate the effect of discrete load patterns in LECs' operation. The objective of LEC's operating cost with its

constraints is defined as follows [1]:

$$\Phi_{LEC,k} = \sum_s \pi_s \Phi_{k,s} + \beta \left(\xi_k + \frac{1}{1-\alpha} \sum_s \pi_s \eta_{k,s} \right) \quad (4)$$

$$\begin{aligned}\Phi_{k,s} = \sum_{t\in\Omega_T} \big[& P^{im}_{k,t,s}\lambda^{im}_{k,t,s} - P^{ex}_{k,t,s}\lambda^{ex}_{k,t,s} \\ & + \lambda^{o\&m,ess}_{k,t,s}(P^{ch}_{k,t,s} + P^{dh}_{k,t,s}) + \sum_{\widehat{k}\neq k} (\lambda^{ptp}_{k,t,s} + \lambda^{nuc}_{k,t,s}) P^{by}_{k,\widehat{k},t,s} \\ & - \sum_{\widehat{k}\neq k} (\lambda^{ptp}_{k,t,s} - \lambda^{nuc}_{k,t,s}) P^{sl}_{k,\widehat{k},t,s} + \lambda^{dg}_{k,t,s} P^{dg}_{k,t,s} \\ & + \lambda^{o\&m,pv}_{k,t,s} P^{pv}_{k,t,s} + \lambda^{o\&m,wt}_{k,t,s} P^{wt}_{k,t,s} \big] \quad k \in \Omega_{LEC} \end{aligned} \quad (5)$$

$$\eta_{k,s} \geq 0 : \pi^{CVaR,1}_{k,s} \quad \forall s \in \Omega_S \quad (6)$$

$$\eta_{k,s} \geq \pi_s \Phi_{k,s} - \xi_k : \pi^{CVaR,2}_{k,s} \quad \forall s \in \Omega_S \quad (7)$$

The objective (4) consists of two terms: first term is the expected operating cost of LEC and second term is CVaR cost (CVaR_α), multiplied by a weighting factor β. The first term of (4) is further decomposed into six terms as described in (5), where the first and second terms refer to import/export costs to/from the LEC. Third term is the operating/maintenance (O&M) costs of ESS, fourth/fifth terms are the P2P cost for buying/selling the power among the LECs. Six term defines the DG costs, and seven/eight terms are O&M cost of PV and WT. CVaR_α term of objective (4) describes the risk behavior of LEC due to uncertainty of loads, PV and WT and market price. This enforces the LEC to make risk-averse decisions to avoid high exposure of uncertainty. The CVaR measures the expected value of cost over $(1-\alpha)\times 100\%$ for a given confidence interval α to consider the risk and is augmented by constraints (6)-(7) for its linear formulation [1]. The weighted factor β in CVaR_α term is used to model the trade-off between the expected cost and risk cost, where low value (i.e., $\beta = 0$) describe risk-neutral and high value (i.e., $\beta = 1$) models high risk-averse behavior. The constraints of embedded resources/ loads in the LECs are defined as follows:

a) Flexible Load Constraints : The constraints of aggregated flexible loads in LEC are defined as follows:

$$\underline{P}^{fl}_{k,t} \leq P^{fl}_{k,t,s} \leq \overline{P}^{fl}_{k,t} \quad k \in \Omega_{LEC}, t \in \Omega_T, s \in \Omega_S \quad (8)$$

$$P^{fl}_{k,t,s} - P^{fl}_{k,t-1,s} \leq P^{f,ru}_{k,t} \quad k \in \Omega_{LEC}, t \in \Omega_T, s \in \Omega_S \quad (9)$$

$$P^{fl}_{k,t-1,s} - P^{fl}_{k,t,s} \leq P^{fl,rd}_{k,t} \quad k \in \Omega_{LEC}, t \in \Omega_T, s \in \Omega_S \quad (10)$$

$$\sum_{t\in\Omega_T} P^{fl}_{k,t,s} = E^{fl}_{k,t,s} \quad k \in \Omega_{LEC}, t \in \Omega_T, s \in \Omega_S \quad (11)$$

Constraint (8) defines the upper/lower bound of flexible load at time t for scenarios s of kth LEC. Constraints (9)-(10) describe the ramp up/down limits. Constraint (11) describes the total flexible energy consumed for a day and is set to the total energy consumption before flexibility operation.

2) ESS Constraints: The constraints of ESS are defined as follows [17]:

$$0 \leq P^{ch}_{k,t,s} \leq \overline{P}^{ch}_{k,t} \delta^{ch}_{k,t,s} \quad \forall k, \forall t, \forall s \quad (12)$$

$$0 \leq P^{dh}_{k,t,s} \leq \overline{P}^{dh}_{k,t} \delta^{dh}_{k,t,s} \quad \forall k, \forall t, \forall s \quad (13)$$

$$\delta^{ch}_{k,t,s} + \delta^{dh}_{k,t,s} \leq 1 \quad \forall k, \forall t, \forall s \quad (14)$$

$$\underline{SC}_{k,t} \leq SC_{k,t,s} \leq \overline{SC}_{k,t} \quad \forall k, \forall t, \forall s \quad (15)$$

$$SC_{k,t+1,s} = SC_{k,t,s} + \frac{\eta^{ch}_k P^{ch}_{k,t,s}}{E^R_{k,t}} + \frac{P^{dh}_{k,t,s}}{\eta^{dh}_k E^R_{k,t}} \quad (16)$$

$$SC_{k,t+1,s} = SC_{k,T,S} \quad \forall k, \forall s \quad (17)$$

Constraints (12)-(13) describe the charging/discharging power limits of ESS. These charging/discharging power are exclusive at time t, described by constraint (14). The limits of state of charge (SOC) are defined in constraint (15). Constraint (16) defines the SOC relationship between next and predecessor SOC and charge/discharge power of current state. The initial and final SOC condition is described in constraint (17).

a) DG Constraints: The operational conditions of DGs, such as upper/lower and ramp up/down limits are defined in the constraints (18)-(20) as follows [1]:

$$\underline{P}^{dg}_{k,t,s} \leq P^{dg}_{k,t,s} \leq \overline{P}^{dg}_{k,t} \quad \forall k, \forall t, \forall s \quad (18)$$

$$P^{dg}_{k,t,s} - P^{dg}_{k,t-1,s} \leq P^{dg,ru}_{k,t} \quad \forall k, \forall t, \forall s \quad (19)$$

$$P^{dg}_{k,t-1,s} - P^{dg}_{k,t,s} \leq P^{dg,rd}_{k,t} \quad \forall k, \forall t, \forall s \quad (20)$$

b) Renewable Constraints: Constraint (21)-(23) defines the renewable energy resources' (RES) (i.e., PV and WT) operation conditions. These RES are assumed to controllable and dispatchable using the renewable technologies.

$$0 \leq P^{pv}_{k,t,s} \leq \overline{P}^{pv}_{k,t} \quad \forall k, \forall t, \forall s \quad (21)$$

$$0 \leq P^{wt}_{k,t,s} \leq \overline{P}^{wt}_{k,t} \quad \forall k, \forall t, \forall s \quad (22)$$

$$\sum_{t\in\Omega_T} (P^{pv}_{k,t,s} + P^{wt}_{k,t,s}) \geq \gamma \sum_{t\in\Omega_T} (\overline{P}^{pv}_{k,t} + \overline{P}^{wt}_{k,t}) \quad \forall k, \forall s \quad (23)$$

c) P2P Constraints: The constraints of P2P energy transaction among LECs are defined as follows [1]:

$$0 \leq P^{by}_{k,\widehat{k},t,s} \leq \overline{P}^{by}_{k,t,s} \delta^{by}_{k,\widehat{k},t,s} \quad \forall k, \forall t, \forall s \quad (24)$$

$$0 \leq P^{sl}_{k,\widehat{k},t,s} \leq \overline{P}^{sl}_{k,t} \theta^{sl}_{k,\widehat{k},t,s} \quad \forall k, \forall t, \forall s \quad (25)$$

$$\delta^{by}_{k,\widehat{k},t,s} + \delta^{sl}_{k,\widehat{k},t,s} \leq 1 \quad \forall k, \forall t, \forall s \quad (26)$$

$$\sum_k \sum_{\widehat{k}\neq k} P^{by}_{k,\widehat{k},t,s} = \sum_k \sum_{\widehat{k}\neq k} P^{sl}_{k,\widehat{k},t,s} \quad \forall t, \forall s \quad (27)$$

Constraints (24)-(27) describe the P2P operation. Constraints (24)-(25) define the maximum P2P power transaction to/from the LEC. Constraint (26) describes exclusive operation of buying and selling of power from/to the LEC using binary variables at time t. The total buying and selling in P2P operation is defined in constraint (27).

d) LEC to Grid Transaction Constraints: The constraints of LEC to/from grid power transaction are defined as follows:

$$0 \leq P^{im}_{k,t,s} \leq \overline{P}^{im}_{k,t}\delta^{im,p}_{k,t,s} \quad \forall k, \forall t, \forall s \tag{28}$$

$$0 \leq P^{ex}_{k,t,s} \leq \overline{P}^{ex}_{k,t}\delta^{ex,p}_{k,t,s} \quad \forall k, \forall t, \forall s \tag{29}$$

$$\delta^{im,p}_{k,t,s} + \delta^{ex,p}_{k,t,s} \leq 1 \quad \forall k, \forall t, \forall s \tag{30}$$

Constraints (28)-(29) describe the bound limits of imported/exported active power from/to the grid by the LEC. This operation is exclusively defined using constraint (30). Likewise constraints can be written for reactive import/export power.

e) LEC Power Balance Constraints: The active and reactive power balance conditions of LEC are defined in constraints (31)-(32) as follows:

$$P^{ch}_{k,t,s} + P^{il}_{k,t,s} + P^{fl}_{k,t,s} + \sum_{\widehat{k}\neq k} P^{sl}_{k,\widehat{k},t,s} + P^{ex}_{k,t,s} - P^{im}_{k,t,s} - P^{dh}_{k,t,s} - \sum_{\widehat{k}\neq k} P^{by}_{k,\widehat{k},t,s} - P^{dg}_{k,t,s} - P^{pv}_{k,t,s} - P^{wt}_{k,t,s} = 0 \tag{31}$$

$$Q^{ex}_{k,t,s} + Q^{il}_{k,t,s} + Q^{fl}_{k,t,s} - Q^{im}_{k,t,s} = 0 \quad k \in \Omega_{LEC} \tag{32}$$

3) Lower-Level Problem: LSE Cost: The LL problem defines the LSE cost. It optimizes its operating costs in day-ahead operation. The problem is formulated using linearised AC power flows with approximated power losses as follows [18]:

$$\Phi_{LSE,s} = \min \sum_{t\in\Omega_T} [\lambda_{p,t,s}P_{G,t,s} + \lambda_{q,t,s}Q_{G,t,s}] \tag{33}$$

$$P_{G,n,t,s} - P_{L,n,t,s} - \sum_{m\leq n} P^{pl}_{mn,t,s} = \sum_{m\neq n} g_{nm}(e_{n,t,s} - e_{m,t,s}) + b_{nm}(f_{n,t,s} - f_{m,t,s}) : \lambda_{p,n,t,s}, \forall n \in \Omega_N \tag{34}$$

$$Q_{G,n,t,s} - Q_{L,n,t,s} - \sum_{m\leq n} Q^{pl}_{mn,t,s} = \sum_{m\neq n} b_{nm}(e_{n,t,s} - e_{m,t,s}) - g_{nm}(f_{n,t,s} - f_{m,t,s}) : \lambda_{q,n,t,s}, \forall n \in \Omega_N \tag{35}$$

$$|\underline{V}_n|^2 \leq (e_{n,s})^2 + (f_{n,s})^2 \leq |\overline{V}_n|^2 : \underline{\pi}_{v,n,t,s}, \overline{\pi}_{v,n,t,s} \tag{36}$$

$$(P_{nm,t,s})^2 + (Q_{nm,t,s})^2 \leq |\overline{S}_{nm,t}|^2 : \pi_{pf,nm,t,s} \tag{37}$$

$$\underline{P}_{G,n,t} \leq P_{G,n,t,s} \leq \overline{P}_{G,n,t} : \underline{\pi}_{p,n,t,s}, \overline{\pi}_{p,n,t,s} \tag{38}$$

$$\underline{Q}_{G,n,t} \leq Q_{G,n,t,s} \leq \overline{Q}_{G,n,t} : \underline{\pi}_{q,n,t,s}, \overline{\pi}_{q,n,t,s} \tag{39}$$

$$e_{1,t,s} = 1 : \pi_{v,1,t,s}, f_{1,t,s} = 0 : \pi_{v,2,t,s} \tag{40}$$

$$\underline{V}_n \leq e_{n,t,s} \leq \overline{V}_n \tag{41}$$

$$\alpha_c P_{nm,t,s} + \hbar_c Q_{nm,t,s} + \ell_c \overline{S}_{nm,t,s} \leq 0; \ \forall c \in C \tag{42}$$

The objective (33) defines the operating cost of LSE. It is the summation of the active/ reactive power purchasing costs. The linearized active and reactive power balance equation with the approximated power loss are described in constraints (34)-(35) [18]. Constraints (36)-(37) define the voltage and apparent power flow limits. The active and reactive power generation limits are described in constraints (38)-(39). Since the constraints (36)-(37) are quadratic constraints, therefore, a linearized form of these constraints is derived in the constraints (40)-(42). The dual variables of the constraints are marked after the colon. The active and reactive power losses are obtained using a Taylor series [18].

III. Solution Methodology

The suggested bilevel problem is mathematically formulated using EPECs, which solves multiple MPECs problems simultaneously [1], [19]. The EPEC problem transforms bilevel problem into equivalent a single level problem. It incorporates the LL problem into the UL using MPECs. The equivalent single formulation in the compact form using general notation is expressed as follows:

$$\min_{y_k,z} \Phi_{LEC,k}(y_k, y^*_{-k}, \lambda) \tag{43}$$

$$h^{pe}_{ul}(y,z) = 0 \tag{44}$$

$$h^{qe}_{ul,}(y,z) = 0 \tag{45}$$

$$h^{ie}_{ul}(y) \geq 0 \tag{46}$$

$$\nabla_z \Phi_{LSE} - \lambda_{p,s}\nabla_z g^I_{ll} - \lambda_{q,s}\nabla_z g^I_{ll} - \upsilon\nabla_z g^I_{ll} = 0 \tag{47}$$

$$g^{PE}_{ll}(z) = 0 \tag{48}$$

$$g^{QE}_{ll}(z) = 0 \tag{49}$$

$$0 \leq \upsilon \perp gll^I(z) \leq 0 \tag{50}$$

Constraints (43)-(46) represent the UL problem and are marked by ul in the superscript. The state/control variables of UL are confined in y. Constraints (44)-(46) describe active/reactive equality and inequality constraints for different load and sources in kth LEC. Constraints (47)-(50) represent the MPEC of the LL problem and are denoted by ll. The LSE's state variables are denoted by $\Theta = \{P_G, Q_G, e, f\}$. The stationary condition of LSE is described in constraint (47). The active and reactive power flow conditions are denoted in equality constraints (48)-(49). The inequality constraints such as voltage, apparent power flow, and generation limits for the LSE are represented using (50). Further, their associated dual variables are abbreviated by υ. The dual variables of active/reactive equality constraints are denoted by $\lambda = \{\lambda_{p,s}, \lambda_{q,s}\}$. These all control and dual variables are compactly written in $z = \{\Theta, \upsilon, \lambda\}$. Constraints (43)-(50) represent the equivalent single-level EPEC formulation. Since the equivalent formulation has complementary constraints and bi-linear objective terms. Therefore, a linearization procedure is employed for the complementary constraints using Fortuny-Amat transformation [20] and bi-linear terms using McCormick envelopes [21], respectively.

IV. Case Study

The proposed stochastic framework and algorithm are implemented on the modified IEEE-33 bus system [22].

A. Simulation Data

The considered system is divided into four sets of customer classes for analyzing LSE operation in the different classes [22]. Each LEC comprises of various resources/ loads and is connected to bus of DS. The detail of each LEC's formation is summarized in Table I.

The historical data for electricity demand, price, PV and wind power for the year 2018 of the United Kingdom are taken from Ref. [23]. This historical data is scaled to the system

TABLE I
DETAILS OF LEC DATA USED IN THE SIMULATION.

Class	Bus	LEC→LEC bus	E_k^R (kWh)	P_k^{dg} (kW)	P_k^{pv} (kW)	P_k^{wt} (kW)	P_k^{by}/P_k^{sl} (kW)
R	2-10	1→8	500	[0, 150]	[0,500]	-	[0, 150]
C	11-18	2→14	500	[0, 100]	[0,500]	[0,500]	[0, 150]
LI	19-25	3→24	1000	[0, 400]	[0,1000]	[0,1000]	[0, 150]
MI	26-33	4→32	500	[0, 150]	[0,500]	-	[0, 150]

level accordingly. The operation & maintenance (O&M) cost for PV and wind power are referred from [24]. The analysis is performed in day-ahead operation considered 20 scenarios for the stochastic optimization. For uncertainty modeling, a Gaussian copula, multivariate function is used to illustrate dependencies in the uncertainty. Fig. 2 (a)-(b) show the scatter plots of randomly generated variables from Gaussian copulas for 13th hour. Fig. 2 (a) shows the Gaussian copula distribution on uniform scale for each variable with the others variables. Similarly, Fig. 2 (b) shows the dependence of the variables on the actual scale. The figure demonstrates that uncertain variables exhibit varying dependencies for different variables pair.

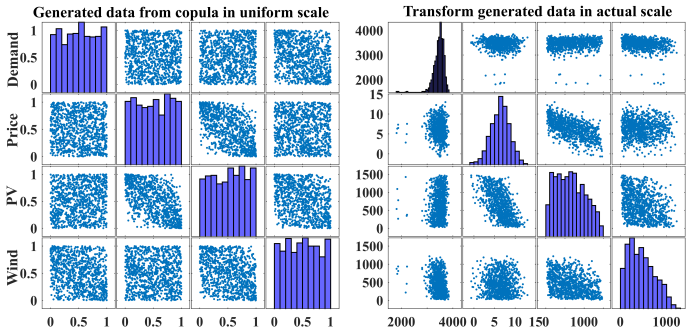


Fig. 2. Generated data from Gaussian copula (a) in Uniform scale and (b) In actual scale.

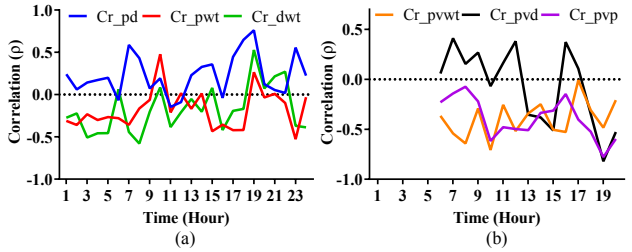


Fig. 3. Correlation of (a) price with demand (Cr_pd) & wind (Cr_pwt) and demand & wind (Cr_dwt) (b) Correlation of PV with wind (Cr_pvwt), demand (Cr_pvd), and price (Cr_pvp).

Fig. 3 (a)-(b) show the correlation for different pairs of variables for each time t. Fig. 3 (a) shows a positive correlation for price with demand (C_pd), while a negative correlation with wind power (C_pwt). Similarly, the correlation of demand with wind power is negative for almost all hours. The correlation of PV power with wind (Cr_pvwt), demand (Cr_pvd) and price (Cr_pvp) is negative except for (Cr_pvd). These different degrees of correlation define the degree of dependence between the variables for each time t. Based on the stochastic optimization, net P2P transaction $(P_k^{by} - P_k^{sl})$ among the LECs over a day is shown in Fig. 4. The figure shows that P2P transaction among LECs exhibits a different magnitude. LEC 1 and LEC 4 mostly buy during over a day in P2P operation, whereas LEC 2 and LEC 3 are more involved in selling over a day.

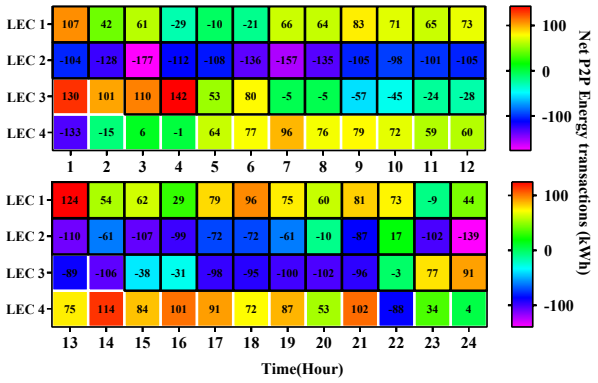


Fig. 4. Net P2P energy transactions among LECs.

The schedules of DG, PV and WT power in the different LECs is shown in Fig. 5 (a). The figure indicates that PV and WT power for all LECs give the maximum output due to low O&M cost compared to DG cost for all day. The DG power output is high for low price hours and low during low price period in LEC 1 and LEC 3. On the other hand, DGs of LEC 2 and LEC 4 gives low output. Likewise energy schedule of ESS for all LECs is shown in Fig. 5 (b). It charges during low pricing and discharge during high price period. Further, it gives different levels of energy consumption for ESSs in LECs.

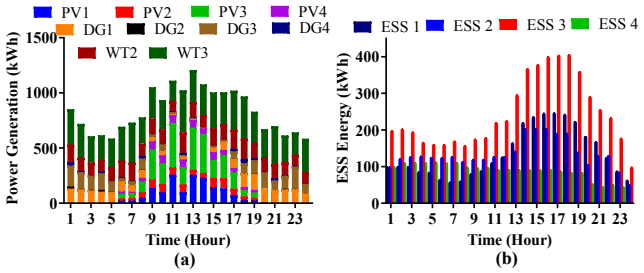


Fig. 5. Optimal schedule of: (a) DG, PV and WT power, and (b) ESS Energy in LECs.

Fig. 6 (a)-(b) show the net active and reactive power transaction between LEC and LSE for a day with and without P2P. It gives different patterns for different LECs. The net active power transaction is mostly negative for all LECs except

LEC 4. This shows that these LEC mostly export the power to grid due to excess generation in LECs as shown in Fig. 6 (a). On the other hand, net reactive transaction are always positive for both P2P case as shown in Fig. 6 (b).

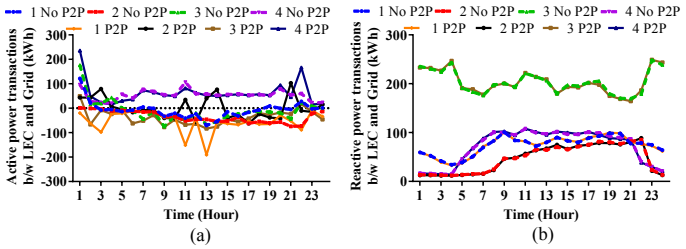


Fig. 6. Active and reactive grid transactions between LEC and Grid with and without P2P/P2P.

The total operating costs of LSE and LEC without and with P2P are presented in Table II. The results show that the cost of LEC and LSE decrease with P2P. This is due to active P2P participation which increases the other terms such as import/export cost, P2P buy/sell cost, import/export demand compared to without P2P.

TABLE II
OVERALL OPERATION COST OF LEC AND LSE WITH/WITHOUT P2P

Index	No P2P	P2P	Index	No P2P	P2P
LEC cost ($)	569.57	516.60	P2P buy cost ($)	0.00	527.23
CVaR cost ($)	113.17	115.34	P2P sell cost ($)	0.00	527.23
NUC cost ($)	0.00	16.35	DER cost ($)	539.58	518.75
Total cost ($)	682.74	631.94	Im demand (kWh)	1965.30	2452.79
Ex cost ($)	84.35	135.75	Ex demand (kWh)	1915.87	3150.86
Im cost ($)	114.34	133.60	LSE cost ($)	4035.89	3988.55

V. CONCLUSION

This paper presents a bilevel stochastic decision framework for the operation of M-LECs in coordination with LSE in DS. It optimizes the total operating cost of M-LECs using DERs, P2P trading, LEC-to-grid transactions, and use the grid-informed DLMP price for grid interaction estimated by LSE. In addition, a Gaussian copula is used to model dependencies in uncertain variables and is incorporated into the objective function using CVaR to account for risk. The simulation results show that active P2P participation of M-LECs increases their coordination with the LSE. This increases P2P trading, LEC-to-grid transactions, and DER utilization in LECs. In addition, the total cost of M-LEC under P2P decreases compared to without P2P.

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