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Markovian-based stochastic operation optimization of multiple distributed energy systems with renewables in a local energy community

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ABSTRACT

Local energy communities (LECs), as locally and collectively organized multi-energy systems, are expected to play an important role in energy transition, since they enable deployment of sustainable energy technologies and consumer engagement, bringing various benefits to the community users and contributing to the overall energy and climate objectives. An LEC may consist of multiple distributed energy systems (DESs), which, interconnected through local grid and heating network, can share power and thermal energy with no costs for community's users. This paper focuses on stochastic daily operation optimization of multiple DESs with renewables in an LEC. The problem is to find the optimized operation strategies of energy devices in each DES, and decide the amount of electrical and thermal energy to be shared among DESs with the objective to minimize the total expected net energy and CO_2 emission cost of the LEC, while meeting given day-ahead demand of community's users. The problem is challenging because of the intermittent and uncertain nature of renewable generation and the coupling of energy devices and energy processes intra and inter DESs. To address these issues, a stochastic mixed-integer linear programming model is established with uncertain renewable generation modeled by a Markovian process to avoid the difficulties and drawbacks associated with scenario-based methods. The problem is solved by using branch-and-cut. Numerical testing results show that the total expected cost of the LEC is reduced by the integrated management of the DESs as compared to the costs attained under other operation modes where there are no interconnections among DESs, demonstrating the potential benefits that can be achieved with LECs through the optimized management of local energy resources aiming to foster efficient use of the available energy. Results also highlight the benefits of the stochastic approach as compared with the deterministic one.

1. Introduction

The worldwide increasing energy demand and environmental problems define the compelling need of energy system decentralization and evolution in the role of final users from passive consumers to active prosumers who both produce and consume energy [1–3]. The ongoing energy transition brings new opportunities for distributed renewable generation integration and deployment, and active involvement of individual consumers to achieve common goals such as reduction of energy costs and environmental impacts. As compared to the traditional centralized energy systems, decentralized local energy systems enable self-sufficiency and sustainability of the energy supply, and research on these systems has considerably increased in recent years [4–8]. In such a context, local energy communities (LECs) play an important role in the energy transition, since they enable deployment of sustainable energy technologies and consumer engagement, bringing various benefits to the community users and contributing to the overall energy and climate objectives [9, 10]. The LEC concept refers to a set of energy users deciding to make common operation choices in terms of satisfying their energy needs, in order to maximize the benefits deriving from this collegial approach, thanks to the implementation of a variety of electricity and heat technologies and energy storages and the optimized management of energy flows. As a result of the integrated approach, LECs are able to fulfil the multi-energy demand of the community users through the optimized operation of local electricity and heat generation and storage by exploiting synergies among the various energy carriers.

By representing a locally and collectively organized energy system, an LEC may consist of multiple distributed energy systems (DESs) interconnected through local grid and heating network to satisfy multi-energy demand (i.e., electricity and thermal) of the users in the LEC

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Nomenclature

A_{PV}	area of installed PV panels (m^2)
C	cooling rate (kW)
$CarbonTax$	total expected daily cost of CO_2 emissions related to the carbon tax ($)
COP	coefficient of performance
$Cost$	total expected net daily cost ($)
E	electric power (kW)
Env	environmental impact in terms of CO_2 emissions (kg CO_2)
G	gas volumetric flow rate (Nm^3/h)
G_{cin}	carbon intensity of gas (kg CO_2/kWh)
H	heat rate (kW)
I	solar irradiance (kW)
k	generation level of the generic technology (kW)
$l_{i,j}$	distance from DES i to user j
LHV^{Gas}	lower heat value of gas (kWh/Nm^3)
N	total number of PV states
P^{CTax}	carbon tax on CO_2 emissions ($/kg$CO_2$)
P^{Gas}	natural gas price ($/$Nm^3$)
$P^{PG,\ buy}$	time-of-day unit price of buying grid power ($/kWh)
$P^{PG,sell}$	time-of-day unit price of selling power back to the grid ($/kWh)
P_{nm}	state transition matrix
t	time (h)
W	weather uncertainty
x	binary decision variable (on/off state of the device)

Greek symbols

$\beta_{i,\ j}$	heat loss factor when transferring heat from DES i to user j
Δt	length of the time interval (h)
η	efficiency
φ	PV state probability

Superscript/Subscripts

AB	auxiliary boiler
ABH	auxiliary boiler for heating
$AChill$	absorption chiller
Bat	battery
$BatC$	battery charging
$BatD$	battery discharging
buy	bought from the power grid
dem	demand
dev	device
ex	exhaust gas
Gas	natural gas
HP	heat pump
HN	heating network
i	index of DES
ICE	internal combustion engine
j	index of end-user
m, n	indices of PV states
max	maximum
min	minimum
out	output
$sell$	sold back to the power grid
sto	stored
TES	thermal storage system
th	thermal
TOT	total

Acronyms

CHP	combined heat and power
DES	distributed energy system
LEC	local energy community
PV	photovoltaic

[11]. In turn, each DES may consist of different types of electrical and heat technologies including renewables and storage systems, which convert and store energy carriers, such as solar energy, gas, electricity, and thermal energy, to satisfy users' multi-energy demand [12, 13]. With multiple DESs connected with each other in an LEC, several energy sources including renewables can be integrated, and waste heat from power generation can be recovered to satisfy thermal demand of the entire LEC. This may offer interesting economic and environmental benefits by fostering local energy sources usage and cross-sector integration at the local level, thereby supporting the efficient use of the available energy. Since DESs can share power and thermal energy with no costs, they are also beneficial to the grid operators since higher self-consumption levels from prosumers cause less problems for peaking loads or renewable energy curtailment. To achieve these benefits, the daily operation of the multiple DESs in the LEC is crucial. The multiple DESs should be coordinated considering energy cost and environmental impacts to satisfy local multi-energy demand. The problem is challenging due to the intermittent nature of renewables, and the coupling of energy devices and energy processes intra and inter DESs. Such challenges require novel approaches to optimally operate local generation and storage in the context of multiple DESs while accounting for the stochastic nature of the problem.

Operation optimization of individual DESs has been widely investigated in the literature. Most works in the literature focused on DESs consisting of single technologies as Combined Heat and Power (CHP) systems coupled with storage units, by considering economic aspects through minimization of energy costs [14–18]. When considering energy systems with multiple energy technologies, several works have been also found addressing operation optimization of individual DESs by considering economic and environmental objectives through a deterministic approach [19, 20]. In our previous work [21–23], operation optimization of individual DESs was investigated with a deterministic approach, and a multi-objective approach was developed to take into account economic and environmental aspects.

The assessment of uncertainties in individual DES operation has also received increasing attention recently. A mixed integer linear programming model was developed in [24] for daily operation of a DES with multiple energy technologies to minimize the daily energy cost. The problem was solved by using branch-and-cut, which is powerful for mixed integer linear programming problems, and the impacts of demand and renewable generation uncertainties were analyzed by using the scenario tree method. A methodology for jointly optimizing the sizing and power management of PV household-prosumers, namely, PV power, electric vehicle charging load, household consumption load, battery bank, and power converters was proposed in [25] through probabilistic PV power generation modeling. An economic optimization model for a CHP microgrid system was defined in [26] by considering the random feature of renewables and loads through the chance constrained programming, and an algorithm of particle swarm optimization based on stochastic simulation was used to solve the problem. In [27], a mixed-integer nonlinear model was developed, where generation uncertainties of wind and photovoltaics (PV) were assessed through a set of scenarios. The problem was solved by using a metaheuristic algorithm. However, selecting an appropriate number of scenarios while accounting for model accuracy, solution feasibility, and computational efficiency is challenging. Moreover, the quality of the solution obtained by using the metaheuristic algorithm cannot be quantified.

When also considering the environmental objective in the operation optimization problem of individual DESs, a stochastic model was established in [28] to minimize both energy costs and CO_2 emissions, where renewable generation and demand uncertainties were modeled by using the scenario method. The resulting stochastic problem was solved by using a teaching-learning-based optimization algorithm. In [29], a stochastic model was developed for optimized operation of a DES considering both economic and environmental objectives. To model uncertain parameters at both supply and demand sides, a set of scenarios were generated through the roulette wheel mechanism and Monte Carlo simulation method. The multi-objective optimization problem was solved by using branch-and-cut. In [30], renewables uncertainties where modeled by a Markovian process, and a mixed integer linear programming model was established to minimize the total energy and emission cost of a microgrid through optimized operation. Branch-and-cut method was used to solve the optimization problem.

Some efforts have been also done for addressing the interactions among multiple microgrids for operation optimization and distributed control purposes, by mainly focusing on the electrical energy carrier [31–33]. When considering also the thermal energy carrier, in [34], an online decentralized and cooperative dispatch algorithm was developed for multi-microgrids with the aim to minimize the overall cost of the community. In the configuration under study, the thermal energy carrier was considered only within the individual microgrids through the CHP technology, and only electricity sharing among the multi-microgrids was addressed thereby neglecting thermal interactions among the systems. A similar approach was established in [35], where a cooperative model predictive control framework was established for urban districts comprising multiple microgrids sharing certain distributed energy resources. The operation of the microgrids were optimized through a deterministic approach with the aim to achieve a common goal such as the minimization of energy exchanged with the distribution grid and the overall energy costs, and the energy management problem was solved through model predictive control in combination with mixed integer linear programming. Environmental impacts assessments were missing in the aforementioned studies.

In the above literature, the operation optimization problem was addressed on the one hand by considering individual DESs, and on the other hand by addressing interactions among multiple DESs from the electrical point of view and by neglecting environmental aspects. The possible benefits for both energy costs and emissions deriving from exploiting synergies among interconnected DESs through electricity and thermal energy sharing within an LEC were not investigated. Also, these studies lack a comprehensive and integrated approach for the optimized daily operation of local electrical and thermal generation and storage in an LEC by considering the community's users as the only beneficiaries of this collegial approach established to manage local resources. For a DES, the multiple energy generation, conversion and storage technologies are lumped, and it is thus not possible to investigate the benefits and impacts on both costs and emissions of potential synergies among interconnected DESs within an LEC. The advantage to extend the optimization framework to multiple DESs (each of them associated to a specific user) lies in the possibility to exploit synergies among the multiple generation, conversion and storage sources, and among various energy carriers to minimize costs and emissions while satisfying the given day-ahead demand of community's users. In this way, it is possible to increase the flexibility of the entire system. Indeed, when users cooperate through sharing energy for satisfying their needs, which is behind the concept of an LEC, more energy options become feasible at the community level, and both energy costs and CO_2 emissions can be minimized through the optimized operation.

Preliminary results presented in [36], are extended in the present paper. In detail, in [36], the operation optimization problem for multiple DESs was addressed through a deterministic approach without considering the stochastic nature of renewables, which is a key issue for distributed renewable generation integration and deployment. In this paper, the goal is to establish a mathematical model for stochastic day-ahead operation optimization of multiple DESs in an LEC, with the aim to minimize the expected net energy cost and CO_2 emission cost by considering carbon tax, while satisfying time-varying power, heat and cooling demands of the users in the LEC. In each DES, several distributed energy devices are considered, such as PV, CHP, heat pump, absorption chiller, boiler, battery and thermal energy storage systems. The DESs are interconnected and can share electricity provided by their CHPs through the local grid, and thermal energy through the heating network. The scheme of the LEC under consideration is shown in Fig. 1.

The problem is to decide the daily operation strategies of the energy devices in each DES and the amount of electrical and thermal energy shared across DESs with the aim to minimize the total daily cost of the

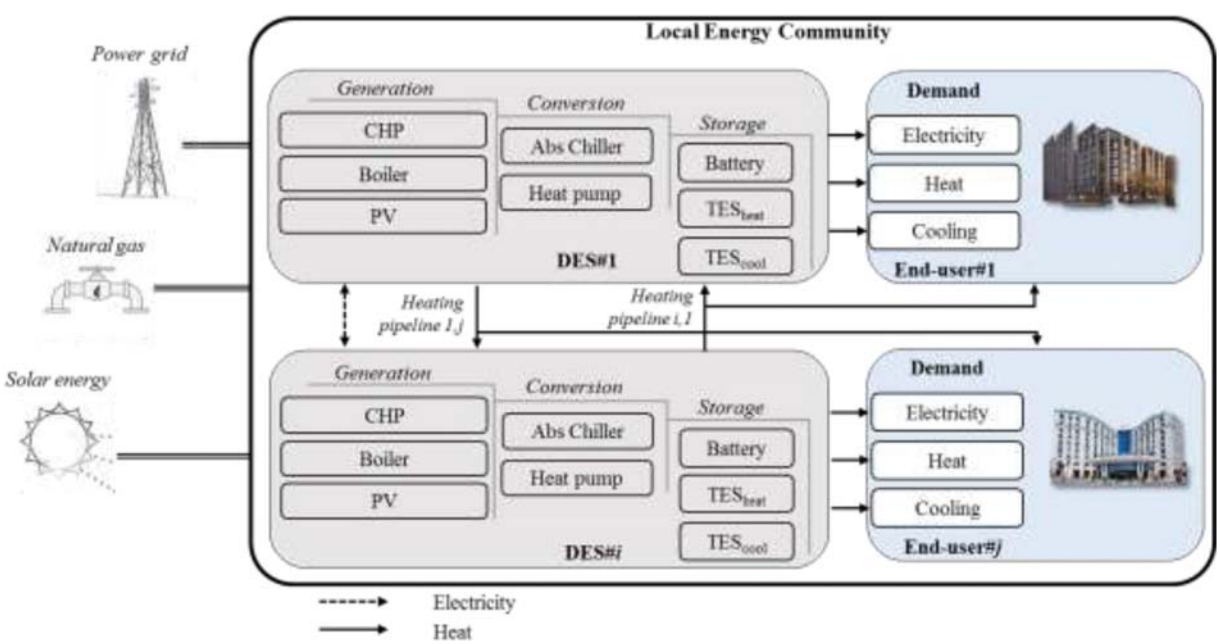


Fig. 1. Scheme of the LEC under consideration.

LEC. It is challenging due to the intermittent and uncertain behaviour of PV generation. In addition, the devices in each DES convert and store various energy carriers with different efficiencies or environmental impacts. Therefore, energy devices and energy processes are coupled within individual DESs, and across DESs because of electricity sharing through local grid and thermal energy sharing through the heating network with thermal losses. To overcome such difficulties, a stochastic mixed integer linear programming model is established with the detailed modeling of energy devices and interactions intra and inter DESs, while integrating the intermittent and uncertain PV generation through a Markov-based model to avoid the difficulties and drawbacks associated with scenario-based methods. The problem is then solved by using branch-and-cut.

The main contributions of this paper are summarized as follows:

- A novel linear model is established for stochastic day-ahead operation optimization of multiple DESs with renewables in an LEC, considering both economic and environmental aspects and considering the community's users as the only beneficiary of this collegial approach.
- The mathematical formulation established addresses the interactions of the various energy carriers within each DES, e.g., electricity, gas, thermal energy, as well as the electrical and thermal interactions among the DESs in the LEC, and the uncertain renewable generation modeled by a Markovian process to avoid the difficulties and drawbacks associated with scenario-based methods.
- The proposed optimization framework is scalable and flexible for adaptation to a number of real contexts thanks to the wide variety of generation, conversion and storage technologies considered and the general mathematical formulation established. This framework can thus represent a valid tool to provide support to decision-makers in understanding the benefits derived by a collegial approach established to manage local energy resources.

An LEC located in U.S is considered for the case study, where there are multiple DESs associated with buildings belonging to residential and commercial sectors. Numerical testing results attained for a winter day and a summer day demonstrate the effectiveness of the method for guarantying the economic and environmental sustainability of the LEC. By comparing four different DES operation modes in the LEC, it is found that the interconnected DESs have the best economic and environmental performances, whereas when DESs are independent and operate in the islanded mode, both the economic and the environmental performances dramatically reduce. Moreover, the results highlight that by accounting for the uncertainties of PV generation through the Markov-based approach, the total expected daily net energy cost of the LEC reduces by 43.7-71.1% as compared with that found through the deterministic approach.

In the following, the stochastic mixed integer linear programming model is established for operation optimization of multiple DESs in an LEC in Section 3. The numerical testing results are presented in Section 4. Conclusions and outlook are discussed in Section 5.

2. Problem formulation

The detailed energy flows among the multiple DESs in the LEC under consideration are shown in Fig. 2 below.

The DESs have their own energy devices, and have the possibility to share power provided by the CHPs via the pre-existing local grid, and the heat recovered from CHPs via the heating network. Heat losses within DESs are not considered, whereas heat losses across DESs are assumed to be a function of the distance of two DESs. The distance between the DES i and the associated end-user j (i.e., $i = j$), is assumed null, whereas the distance among the various DESs is assumed known.

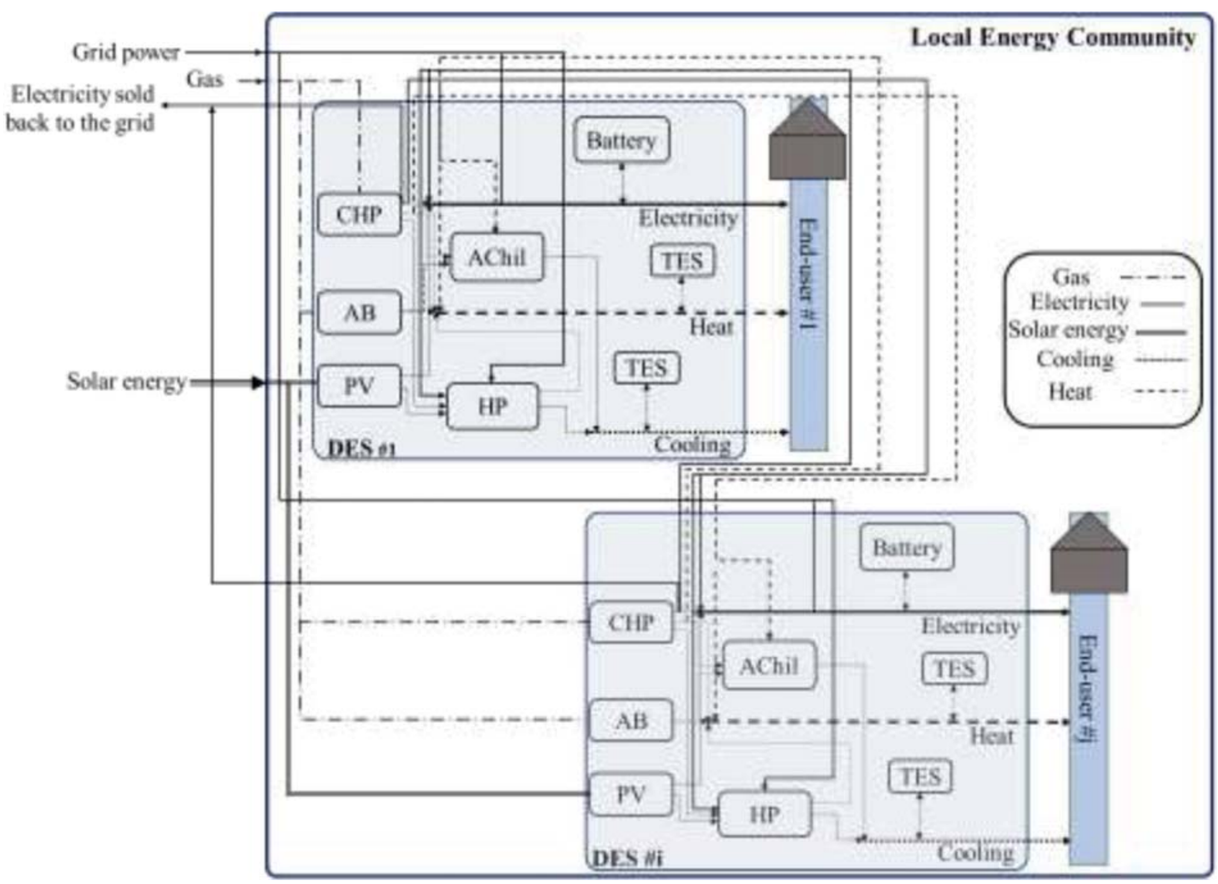


Fig. 2. Energy flows intra and inter DESs in the LEC under consideration.

For each user: (1) power demand can be met by grid power, CHP, PV and battery of its own DES, and CHPs in other DESs through the local grid; (2) heat demand can be met by the CHP, heat pump, boiler, and thermal storage of its own DES, and CHPs in other DESs via the heating network; and (3) cooling demand by the absorption chiller, heat pump, and thermal storage of its own DES. The absorption chiller can be powered by the thermal energy provided by the boiler and CHP in the corresponding DES, and by CHPs in other DESs via the heating network. In addition, DESs can sell the excess power from their CHPs back to the utility grid.

With the consideration of intermittent and uncertain PV generation, a stochastic mixed integer linear programming model is established in this section for the operation optimization problem of the multiple DESs in the LEC. The constraints for energy devices and energy balance are discussed in Sections 3.1 and 3.2, respectively. The objective is presented in Section 3.3, whereas the optimization method that is used to solve the resulting problem is briefly introduced in Section 3.4.

2.1. Constraints of energy devices

For energy devices, their energy efficiencies are assumed constant for simplicity. For all the devices except for PV, battery and thermal storage, there are a set of binary variables x (x is equal to 1 when the device is on) to present the device on/off status, and a set of continuous decision variables E (H/C for thermal devices) to represent the generation level. In DES i, if device dev is on ($x_i^{dev}(t)$ is 1), its generation level $E_i^{dev}(t)$ has to be within the minimum allowed $E_{i,}^{dev,min}$ and the maximum $E_{i,}^{dev,max}$, and 0 otherwise, i.e.,

$$x_i^{dev}(t)\cdot E_i^{dev,\min} \le E_i^{dev}(t) \le x_i^{dev}(t)\cdot E_i^{dev,\max}. \tag{1}$$

For each device, the other constraints are presented below.

2.1.1. Constraints of the auxiliary boiler

To quantify natural gas consumption in the boiler, the volumetric flow rate $G_i^{AB}(t)$ is modeled as:

$$G_i^{AB}(t) = H_i^{AB}(t)/(\eta_i^{AB}\cdot LHV^{Gas}), \tag{2}$$

where η_i^{AB} is the efficiency of the boiler, and LHV^{Gas} is the natural gas lower heat value. This amount of heat is subdivided into two parts (continuous decision variables): one is $H_i^{ABH}(t)$ to directly meet heat demand; and the other one is $C_i^{AB}(t)$ to meet cooling demand by the absorption chiller:

$$H_i^{AB}(t) = H_i^{ABH}(t) + C_i^{AB}(t). \tag{3}$$

The gas combustion in the boiler causes CO_2 emissions, which are evaluated as $Env_i^{AB}(t)$:

$$Env_i^{AB}(t) = G_i^{AB}(t)\cdot LHV^{Gas}\cdot G^{cin}, \tag{4}$$

where G^{cin} is the carbon intensity of natural gas.

2.1.2. Constraints of the reversible heat pump

The heat pump has two modes to work in order to satisfy heat and cooling demands in different seasons. To produce heat $H_i^{HP}(t)$ under the heat mode, the power consumption $E_i^{HP}(t)$ is given by:

$$E_i^{HP}(t) = H_i^{HP}(t)/COP_i^{HP}, \tag{5}$$

where COP_i^{HP} is the coefficient of performance of the heat pump in the heat mode. Note that in (5), $H_i^{HP}(t)$ is a continuous decision variable. Under the cooling mode, the modeling is similar to the above.

2.1.3. Constraints of the CHP

The internal combustion engine in the CHP system generates power to meet the power demand, whereas the associated exhaust heat can be recovered to satisfy the thermal demand [21]. The corresponding constraints are presented below.

To provide power $E_i^{ICE}(t)$ (a continuous decision variable), the natural gas volumetric flow rate $G_i^{ICE}(t)$ is given by:

$$G_i^{ICE}(t) = E_i^{ICE}(t)/(\eta_i^{ICE}\cdot LHV^{Gas}), \tag{6}$$

where η_i^{ICE} is the electrical efficiency of the CHP.

The recovered heat $H_i^{ICEex,TOT}(t)$ from the CHP is:

$$H_i^{ICEex,TOT}(t) = E_i^{ICE}(t)\cdot\eta_i^{ICE,th}/\eta_i^{ICE}, \tag{7}$$

where $\eta_i^{ICE,th}$ is the thermal efficiency of the CHP.

Similar to the boiler, the amount of recovered heat is subdivided into four parts (continuous decision variables): (1) $H_i^{ICEex}(t)$ to directly meet heat demand; (2) $C_i^{ICEex}(t)$ to meet cooling demand by the absorption chiller; (3) $H_{i,j}^{ICEex}(t)$ to share with other DESs for heating purposes through the heating network; (4) and $C_{i,j}^{ICEex}(t)$ to share with other DESs for cooling purposes through the heating network:

$$H_i^{ICEex}(t) + C_i^{ICEex}(t) + \sum_{j;j\neq i}(H_{i,j}^{ICEex}(t) + C_{i,j}^{ICEex}(t)) = H_i^{ICEex,TOT}(t). \tag{8}$$

The gas combustion in the CHP also causes CO_2 emissions, which are evaluated as $Env_i^{ICE}(t)$

$$Env_i^{ICE}(t) = G_i^{ICE}(t)\cdot LHV^{Gas}\cdot G^{cin}. \tag{9}$$

2.1.4. Constraints of the absorption chiller

With heat source coming from the boiler, the CHP and the other DESs, the cooling rate $C_i^{AChil}(t)$ provided by the absorption chiller is formulated as:

$$C_i^{AChil}(t) = \left(C_i^{ICEex}(t) + C_i^{AB}(t) + \sum_{j;j\neq i} C_{i,j}^{ICEex}(t)\cdot\eta_{i,j}^{HN}\right)COP_i^{AChil}. \tag{10}$$

In the above, COP_i^{AChil} is the chiller's coefficient of performance, and $\eta_{i,j}^{HN}$ is the heating network efficiency from DES i to user j. Heat losses in the heating network are considered to be a function of the distance among DESs and users. The related efficiency $\eta_{i,j}^{HN}$ is evaluated as follows:

$$\eta_{i,j}^{HN} = 1 - \beta_{i,j}\cdot l_{i,j}, \tag{11}$$

where $\beta_{i,j}$ is the heat loss factor when transferring heat from DES i to user j, and $l_{i,j}$ represents the distance from DES i to user j. Note that if $i=j$, then $l_{j,i}=0$, and no heat losses occur.

2.1.5. Constraints of the PV power generation

The ideal PV power generation behaves like a sinusoidal wave during day time and has zero values for night hours [37, 38]. Amplitude and frequency of the wave are functions of the size and location of the PV plant, and seasons. However, PV generation can strongly vary with weather conditions, e.g., clouds. To overcome the computational efforts caused by the usage of scenario-based methods, a Markov-based model is established based on our previous work [30]. Following the real case studies in [39, 40], it is assumed that weather uncertainties are a Markovian process with N states (proportional to ideal weather conditions), and state m is denoted as W_m. To balance modeling accuracy and computation efficiency, the total state number is determined based on historical data.

By considering historical data, if n was the previous state, then the probability that m is the current state can be obtained as [41],

$$P_{nm} = \frac{\textbf{observed transitions from state } n \textbf{ to } m}{\textbf{occurrences of state } n}. \tag{12}$$

By following this approach, the state transition matrix P_{nm} is obtained. It should be updated by integrating latest weather forecasting. Also a transition matrix is needed for each season due to the different seasonal behaviors.

According to the weather conditions modeled above, PV power generation ${E_{i,m}}^{PV}(t)$ is modeled as follows:

$$E_{i,m}^{PV}(t) = E_i^{PV} W_m. \tag{13}$$

In the above, ideal PV generation E_i^{PV} is evaluated as [42, 43]:

$$E_i^{PV} = A_i^{PV} \cdot \eta_i^{PV} \cdot \max_t (I(t)), \tag{14}$$

where ${A_i}^{PV}$ is the total area of the PV plant; ${\eta_i}^{PV}$ is the electrical efficiency; and $I(t)$ is the solar irradiance.

The probability $\varphi_m(t)$ that PV generation is ${E_{i,m}}^{PV}(t)$ at time t is derived as the weighted sum of the probabilities of all the states at time (t - 1), where the weights are different transitions:

$$\varphi_m(t) = \sum_{n=1}^{N} P_{nm}\varphi_n(t-1). \tag{15}$$

The probabilities of future time intervals can be derived based on the initial state and the transition matrix.

2.1.6. Modeling of boilers, heat pumps, CHPs, and chillers based on PV states

By modeling PV generation as a Markov process, the other devices in each DES are also modeled as Markov processes correspondingly, where their states depend on PV states. Therefore, the generation levels of boilers, heat pumps, CHPs and chillers, and the amount of buying and selling grid power are all functions of PV states. Take the combustion engine of CHP in DES i as an example. For each PV state m, the engine has a corresponding generation level ${E_{i,m}}^{ICE}(t)$. The generation capacity constraint for the engine is revised as follows:

$$E_i^{ICE,\min} \le E_{i,m}^{ICE}(t) \le x_i^{dev}(t) \cdot E_i^{ICE,\max}. \tag{16}$$

As compared with Eq. (1), the constraint is applied to every DES index i, time index t, and PV state index m.

The same is valid for the other devices.

2.1.7. Constraints of the battery

For the battery, the amount of power charging and discharging depends on PV states. At time t, the state of charge under PV state m is denoted as ${E_{i,m}}^{Bat}(t)$. The standard one dimensional system dynamics on state of charge in the literature is extended to a two dimensional one on the state of charge and PV states as follows:

$$\begin{aligned} &E_{i,m}^{Bat}(t) = E_{i,m}^{Bat}(t-1) + E_{i,m}^{BatC}(t)\eta_i^{BatC} - E_{i,m}^{BatD}(t)/\eta_i^{BatD}, \\ &E_{i,m}^{BatC}(t) \le E_{i,m}^{PV}(t),\ \forall\ n,\ \forall\ m \in \{m|\varphi_m(t) \ne 0,\ P_{nm} \ne 0\}, \end{aligned} \tag{17}$$

where ${\eta_i}^{BatC}$ and ${\eta_i}^{BatD}$ are the charging and discharging efficiencies, respectively. Note that in (17), the amounts of power charging and discharging the battery are continuous decision variables of the battery. Also, it is assumed that charging and discharging the battery simultaneously is not possible, and the modeling of this constraint is omitted for brevity.

2.1.8. Constraints of the thermal storage systems

The amount of energy ${H_{i,m}}^{Sto}(t)$ stored in the thermal storage at time t can be modeled as:

$$\begin{aligned} H_{i,m}^{Sto}(t) = {} & H_{i,m}^{Sto}(t-1) \cdot \eta_i^{TES} \\ & + \Delta t (H_{i,m}^{TESIn}(t) - H_{i,m}^{TESOut}(t)),\ \forall\ m,\ \forall \\ & n \in \{m|\varphi_m(t) \ne 0,\ P_{nm} \ne 0\}, \end{aligned} \tag{18}$$

where ${\eta_i}^{TES}$ is the thermal storage efficiency, and Δt is the length of a time interval. In (17), the amounts of heat charging ${H_{i,m}}^{TESIn}(t)$ and discharging ${H_{i,m}}^{TESOut}(t)$ are continuous decision variables of the thermal storage.

The thermal storage for cooling is modeled in a similar way.

2.2. Energy balance constraints

In order to satisfy the given time-varying user demands, power, heat and cooling energy balances are established by matching supply and demand.

2.2.1. Power balance

At each time interval and for each PV state with a nonzero probability, the summation of power demand ${E_i}^{dem}(t)$, power required by the heat pump ${E_{i,m}}^{HP}(t)$, charging the battery ${E_{i,m}}^{BatC}(t)$, sent to the other DESs $E_{i,j,m}(t)$, and sold back to the utility grid ${E_{i,m}}^{sell}(t)$, must be satisfied by the summation of power from CHP ${E_{i,m}}^{ICE}(t)$, PV ${E_{i,m}}^{PV}(t)$ and battery ${E_{i,m}}^{BatD}(t)$, collected from the other DESs $E_{j,i,m}(t)$, and bought from the utility grid ${E_{i,m}}^{buy}(t)$, i.e.,

$$\begin{aligned} &E_i^{dem}(t) + E_{i,m}^{HP}(t) + E_{i,m}^{BatD}(t) + E_{i,m}^{sell}(t) + \textstyle\sum_{j:j\ne i} (E_{i,j,m}(t)) \\ &\quad = E_{i,m}^{ICE}(t) + E_{i,m}^{PV}(t) + E_{i,m}^{BatD}(t) + E_{i,m}^{buy}(t) + \textstyle\sum_{j:j\ne i} (E_{j,i,m}(t)), \\ &\textstyle\sum_{j:j\ne i} (E_{i,j,m}(t)) \le E_{i,m}^{ICE}(t),\ \forall\ m \in \{m|\varphi_m(t) \ne 0\}. \end{aligned} \tag{19}$$

In the above, $E_{i,j,m}(t)$, ${E_{i,m}}^{sell}(t)$, $E_{j,i,m}(t)$ and ${E_{i,m}}^{buy}(t)$ are continuous decision variables. Power demand is assumed given.

2.2.2. Heat energy balance

At each time interval and for each PV state with a nonzero probability, the heat demand ${H_i}^{dem}(t)$ must be satisfied by the summation of the heat from CHP ${H_{i,m}}^{ICEex}(t)$, the boiler ${H_{i,m}}^{AB}(t)$, the thermal storage ${H_{i,m}}^{TESOut}(t)$ - ${H_{i,m}}^{TESIn}(t)$, and from other DESs, i.e.,

$$\begin{aligned} H_i^{dem}(t) = {} & H_{i,m}^{ICEex}(t) + H_{i,m}^{AB}(t) + H_{i,m}^{TESOut}(t) - H_{i,m}^{TESIn}(t) \\ & + \sum_{j:j\ne i} \eta_{HN,j,i} \cdot H_{j,i,m}^{ICEex}(t), \\ & \forall\ m \in \{m|\varphi_m(t) \ne 0\} \end{aligned} \tag{20}$$

The cooling energy balance can be modeled in a similar way.

The entire problem is therefore Markovian.

2.3. Objective

The objective is to minimize the total expected daily cost, considered as the sum of the expected net energy cost and the expected emission cost. The expected net energy cost *Cost* consists of three terms, i.e., expected costs of buying gas and grid power, and the expected profit of selling power back to the utility grid, i.e.,

$$\begin{aligned} &Cost \\ &\quad = \sum_i \sum_t \sum_m \varphi_m(t)(P^{Gas} \cdot (G_{i,m}^{ICE}(t) + G_{i,m}^{AB}(t)) + P^{PG,buy}(t) \cdot \\ &\quad E_{i,m}^{buy}(t) - P^{PG,sell}(t) \cdot E_{i,m}^{sell}(t)), \end{aligned} \tag{21}$$

where P^{Gas} is the unit price of gas, and $P^{PG,\ buy}(t)$ and $P^{PG,sell}(t)$ are the time-of-day unit prices of buying power from and selling power back to the utility grid at time t, respectively.

The expected cost of CO_2 emissions due to gas combustion in the boilers and combustion engine of CHPs is quantified through the carbon tax [44], i.e.,

$$CarbonTax = P^{CTax} \cdot \sum_i \sum_t \sum_m \varphi_m(t)(Env_{i,m}^{AB}(t) + Env_{i,m}^{ICE}(t)), \tag{22}$$

where P^{CTax} is the carbon tax on CO_2 emissions. Since the carbon tax related to the grid power is reflected in the price, there is no need to add it again.

The overall objective to be minimized is thus given by $Cost + CarbonTax$.

2.4. Decision variables

The problem (1-22) established above has linear constraints and objective function. As for decision variables, it includes: (1) on/off status and generation levels of every energy device (except for PV, battery and thermal storage); (2) the amount of thermal energy provided by the auxiliary boiler to directly meet heat demand and to meet cooling demand by the absorption chiller; (3) the amount of thermal energy recovered by CHP to directly meet heat demand, to meet cooling demand by the absorption chiller, to share with other DESs for heating purposes through the heating network, and to share with other DESs for cooling purposes through the heating network; (4) the amount of energy charged to and discharged from the battery and thermal storage; (5) the power bought from and sold back to the utility grid; and (6) the amount of electrical energy provided by CHPs to share with other DESs.

2.5. Solution methodology

The problem (1-22) established above is stochastic and linear, and involves both integer and continuous variables. Branch-and-cut, a powerful method for mixed integer linear programming problems, is thus used to solve the problem. In the method, all integrality requirements on integer variables are first relaxed, and the relaxed problem is solved by using linear programming methods. If all integer decision variables have integer values, the solution is also optimal to the original problem. If not, valid cuts that do not cut off feasible integer solutions are added, trying to obtain the convex hull. If the convex hull is obtained, the problem can be solved by linear programming methods without combinatorial difficulties. If the convex hull cannot be obtained, the method relies on time-consuming branching operations. The solution of the relaxed problem provides a lower bound. The method stops when computational time reaches the pre-set stop time or the relative mixed-integer programming gap (relative difference between the objectives of the optimal relaxed solution and current integer solution) falls below the pre-set gap [45].

A detailed flowchart of the optimization problem formulated above is shown in Fig. 3. In detail, given the input data of the model, such as structure of the heating network, user multi-energy demand, energy prices, solar irradiance profiles, carbon intensity and carbon tax, and technical data of energy devices in the multiple DESs, assigned decision variables and established problem constraints, the proposed model, which is stochastic and linear, and involves both integer and continuous variables, allows to obtain the daily operation strategies of the energy devices in each DES and the amount of electrical and thermal energy shared across DESs with the aim to minimize the expected total daily cost of the LEC.

3. Case study

In this case study, an LEC located in U.S. is considered. In this LEC, there are multiple DESs associated to a set of users belonging to residential and commercial sectors, namely midrise apartment, strip mall, supermarket and a cluster of office buildings. A typical winter day in January and a typical summer day in July are considered with hourly time intervals. Input data such as load profiles and energy prices are described in Section 4.1. The corresponding operation optimization

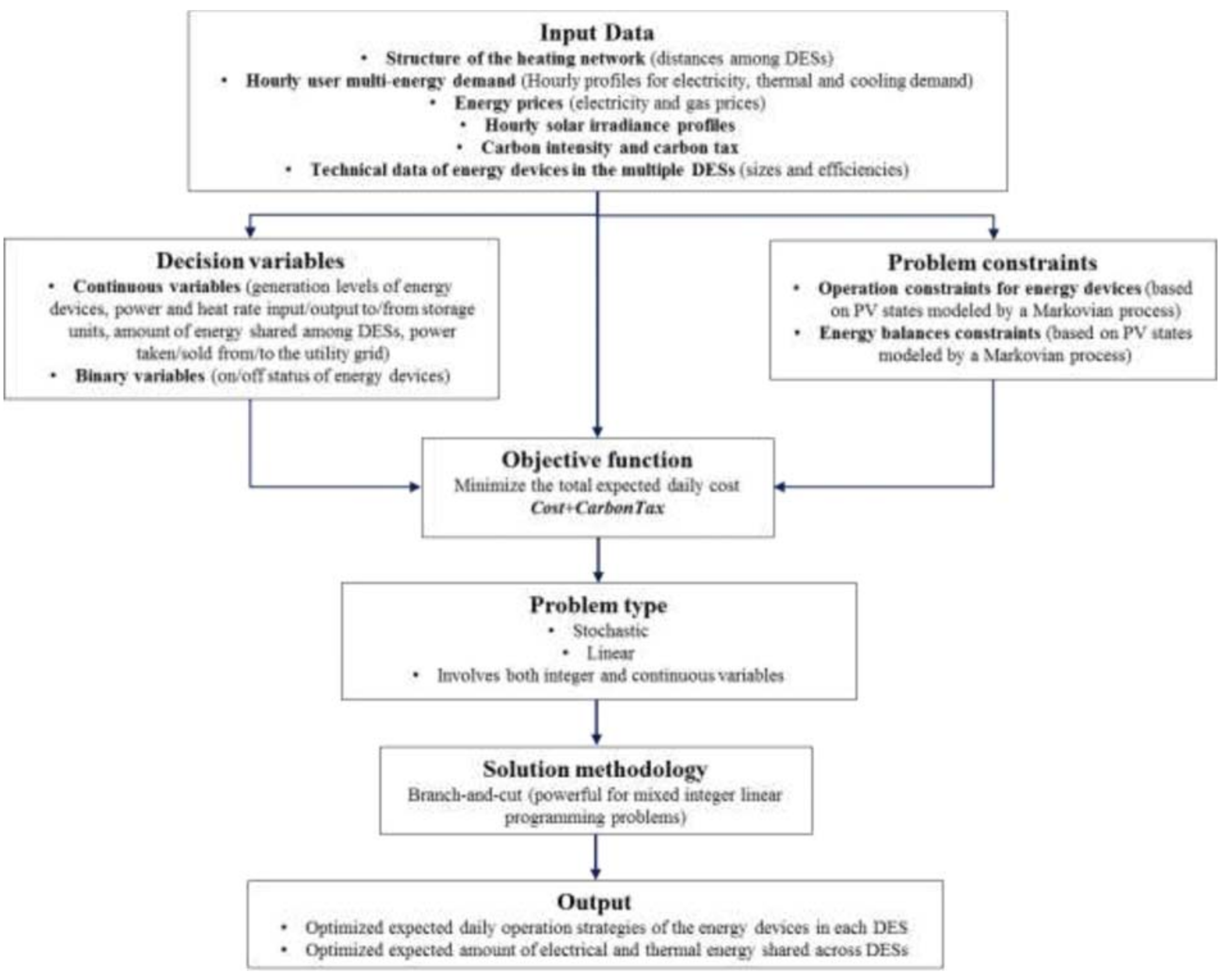


Fig. 3. Flowchart of the stochastic optimization problem.

problems are solved by using IBM ILOG CPLEX Optimization Studio V 12.8.0.0 [45] on a PC with 2.90GHz Intel Core(TM) i7 CPU and 16G RAM. CPLEX is a powerful commercial solver for mixed integer linear programming problems, and is widely used in power industries. For both winter and summer days, DES operation strategies are discussed in Section 4.2, by considering different operation modes. Results and insights for one DES are presented in Section 4.3. In Section 4.4, results obtained by the deterministic approach in both winter and summer days are compared with those obtained with the stochastic approach.

3.1. Model input data

To run the optimization model, the needed input data consists of the structure of the heating network, the hourly energy demand, the energy prices, the hourly values for solar irradiance, the carbon intensity and tax, and the technical data of the energy devices in the DESs.

3.1.1. Structure of heating network

For easy presentation, denote the DESs for super market, strip mall, small office, and midrise apartment as DES1, DES2, DES3 and DES 4, respectively. The heating network is assumed to be a one directional rectangle (i.e., $l_{j,i} \neq l_{i,j}$). The distances from DES1 to DES2, from DES2 to DES3, and from DES3 to DES4 are assumed as 50, 100, 50, and 100 (meters), respectively. Moreover, according to [46], the heat loss factor is assumed equal to 4×10^{-5}.

3.1.2. Energy demand profiles

The profiles of hourly energy demand for the typical winter and summer days in January and July are defined based on [47]. For illustration purposes, the hourly demand profiles of the four end-users in the winter day are shown in Fig. 4a and b for electricity and heat, respectively.

3.1.3. Energy prices

The time-of-day electricity price from the utility grid and the natural gas price are chosen based on the current U.S. market. For grid power, the unit price ($/kWh) is obtained based on EverSource tariff Rate 7 (residential) and 27 (commercial) [48] with simplifications. This unit price does not take into account the demand charge, and the price is assumed to be 2.5 times of the summation of the remaining charges. Also, the monthly customer charge on distribution service is evenly distributed to each day in the month. The price for selling the excess power back to the utility grid is assumed to be equal to 48% of the corresponding buying price of grid power. For natural gas unit price ($/Nm^3), reference is made to the data published by Energy Information Administration [49]. For simplicity, the above prices are assumed the same for the winter and summer cases.

3.1.4. Data on solar irradiance

The solar irradiance hourly profiles are built up based on meteorological data [50]. To define a representative winter day in January, the hourly solar irradiance profile is calculated by averaging the hourly solar irradiance of all days in the month. The hourly solar irradiance profile for the summer day in July is built up in the same way. To evaluate power generation from PV, for each season, a 10-state transition matrix is considered as shown below [37].

$$P_{nm}^{\text{Winter}} = \begin{pmatrix} 0.905 & 0.071 & 0.012 & 0.012 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.109 & 0.691 & 0.164 & 0.036 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.054 & 0.27 & 0.325 & 0.216 & 0.054 & 0.027 & 0.027 & 0.027 & 0 & 0 \\ 0 & 0.04 & 0.44 & 0.24 & 0.2 & 0.04 & 0.04 & 0 & 0 & 0 \\ 0 & 0 & 0.188 & 0.313 & 0.375 & 0.062 & 0 & 0.062 & 0 & 0 \\ 0 & 0 & 0 & 0.333 & 0.111 & 0.334 & 0.111 & 0 & 0.111 & 0 \\ 0 & 0 & 0.111 & 0 & 0.111 & 0.222 & 0.445 & 0.111 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.091 & 0.091 & 0.091 & 0.636 & 0.091 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.1 & 0.1 & 0.7 & 0.1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.077 & 0.923 \end{pmatrix}$$

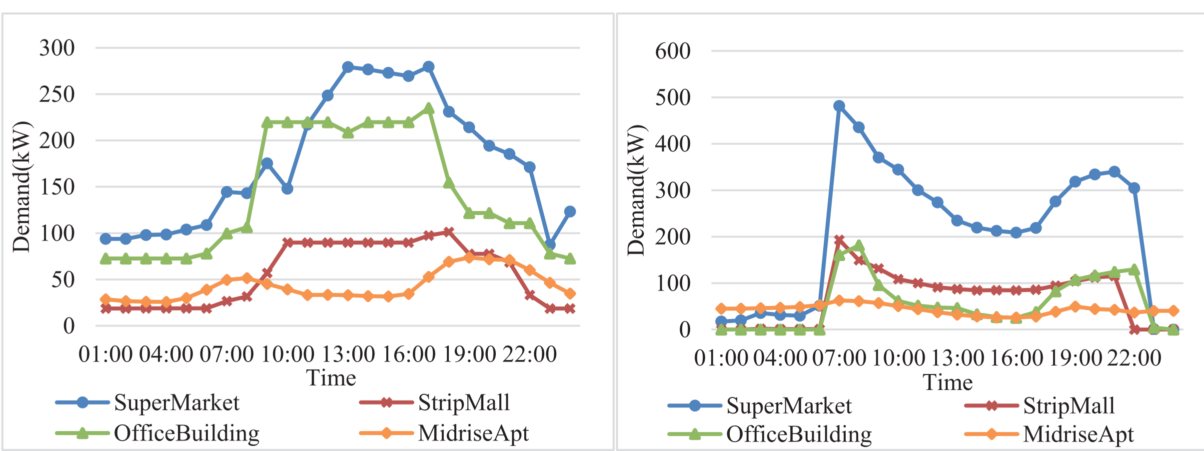
$$P_{nm}^{\text{Summer}} = \begin{pmatrix} 0.862 & 0.124 & 0.014 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.153 & 0.644 & 0.136 & 0.034 & 0.017 & 0 & 0.008 & 0.008 & 0 & 0 \\ 0.041 & 0.219 & 0.467 & 0.178 & 0.041 & 0.027 & 0.027 & 0 & 0 & 0 \\ 0.024 & 0.071 & 0.239 & 0.214 & 0.143 & 0.119 & 0.071 & 0.095 & 0.024 & 0 \\ 0 & 0.059 & 0.147 & 0.088 & 0.235 & 0.354 & 0.088 & 0.039 & 0 & 0 \\ 0 & 0.022 & 0.067 & 0.133 & 0.156 & 0.378 & 0.178 & 0.022 & 0.022 & 0.022 \\ 0 & 0.026 & 0.026 & 0.103 & 0.154 & 0.179 & 0.306 & 0.154 & 0.026 & 0.026 \\ 0 & 0 & 0.029 & 0.057 & 0.057 & 0.029 & 0.2 & 0.342 & 0.257 & 0.029 \\ 0 & 0 & 0 & 0 & 0 & 0.042 & 0.042 & 0.332 & 0.292 & 0.292 \\ 0 & 0 & 0 & 0.067 & 0 & 0 & 0.133 & 0.2 & 0.267 & 0.333 \end{pmatrix}$$

3.1.5. Carbon intensity and carbon tax

For natural gas, its carbon intensity is assumed as 0.202 kg/kWh. The carbon tax in 2015 [44] is considered.

3.1.6. Technical data of energy devices in the DESs

The technical data of energy devices in the four DESs are presented in Table 1.



a b

Fig. 4. (a) Hourly profiles for electricity demand in the winter day. (b) Hourly profiles for heat demand in the winter day.

Table 1
Technical data of energy devices in the four DESs.

	Size (kW) – (kWh)				Efficiency			
	DES1	DES2	DES3	DES4	DES1	DES2	DES3	DES4
Auxiliary boiler	160	65	60	40	0.90	0.9	0.9	0.9
PV panels: m^2	1600	590	1370	430	0.14	0.1	0.1	0.1
Heat pump	430	175	170	60	3.5	3.5	3.5	3.5
CHP (Power)	425	155	355	115	0.34	0.3	0.3	0.3
(Heat)					0.48	0.5	0.5	0.5
Battery (Charge)	200	50	180	30	0.9	0.9	0.9	0.9
(Discharge)					0.9	0.9	0.9	0.9
Thermal storage systems	400	200	300	100	0.9	0.9	0.9	0.9

3.2. Comparison of different operation modes of the DESs in the LEC through stochastic approach

Four operation modes for the multiple DESs in the LEC are analyzed as described below:

- Case *a*: The base case where the multiple DESs can share electricity and thermal energy. They operate in the grid-connected mode and can sell excess electricity back to the utility grid.
- Case *b*: The multiple DESs are independent energy systems, and do not share electricity and thermal energy. They operate in the grid-connected mode and can sell excess electricity back to the utility grid individually.
- Case *c*: The multiple DESs can share electricity and thermal energy. They operate in the islanded mode and cannot sell excess electricity back to the utility grid.
- Case *d*: The multiple DESs are independent energy systems (do not share energy) and operate in the islanded mode.

The results obtained with the stochastic approach are presented below for the winter and summer days.

3.2.1. Optimization results for the LEC in the winter day

The operation optimization problems are solved by using CPLEX, and it takes 5 to 8 seconds. In the winter case, there are 672 binary decision variables and 28,800 continuous decision variables. In total there are 92,404 constraints. The summer case has similar numbers of decision variables and constraints.

The expected values of the total net energy costs with the various terms of the objective function are shown in Table 2 for the four cases in the winter day.

It can be seen that the operation mode in the base case (case *a*) allows to achieve the lower total expected energy cost as compared with other cases. For case *b*, when the DESs are independent energy systems, the total expected net energy cost increases by 2.0% and the expected revenue of selling electricity back to the grid significantly decreases by 97.9%. By exploiting synergies among the DESs in the LEC through sharing electrical and thermal energy, much more electricity can be sold back to the utility grid, resulting in much reduced total expected net cost through increasing the revenue term. This result is consistent with those presented in [35], where in the operation optimization of the multiple microgrids with the aim to minimize the overall energy costs, it was found that the energy cooperation among microgrids has significant economic benefits with respect to the non-cooperative operation strategy. This is due to the fact that fully interconnected microgrids allow that energy surplus in one microgrid can be utilized to compensate for energy deficit in another microgrid, thereby optimizing the use of available local energy resources. Under the islanded mode, the performances of the LEC under case *c* get further worse, and the expected net energy cost increases by 12.2%. Case *d* shows the poorest performances with a cost increase of 14.6% as compared to base case *a*, because there is no possibility to share energy among DESs and to sell excess electricity to the utility grid.

To compare the four operation modes in the winter day, Fig. 5 shows the expected values of: 1) the total electrical load; (2) the total grid power bought from the utility grid; (3) the total electricity sold back to the utility grid, kept for DES for self-use and shared across DESs (from all CHPs); (4) the total electricity generated by all PV systems; and (5) the total electricity discharged by all batteries. Note that for each DES, the total electricity load is equal to the summation of the demand and the electricity consumed by the heat pumps in the multiple DES. For base case *a*, it can be seen that the amount of electricity sold back to the utility grid is larger than case *b*, and this allows to increase the revenue. In these two cases, the total electrical load is almost the same, and electricity from PVs and batteries is also the same. Also, the increase of usage of electricity bought from the utility grid is lower than the increase of the electricity generated by CHPs in case *a* comparing with case *b*. The reason is that DESs can share electricity, thereby allowing to reduce the total expected net energy cost of the LEC. For cases *c* and *d* with DESs operating in the islanded mode, it can be seen that the total electrical load reduces as compared with that found in cases *a* and *b* with DESs operating in the grid-connected mode. This is due to the lower usage of heat pumps to meet the heat demand. This result highlights that the total electrical load varies as a function of the available sources at supply side, since in both cases *c* and *d*, the power supply is limited in the absence of connection to the grid. In fact, in these cases, only CHPs are used to satisfy the electrical demand of the LEC beyond PV systems and batteries. Under the islanded mode, DESs cannot take advantage of low prices grid power in certain hours. This explains the worsening of performances of the LEC in cases *c* and *d* as compared to those found in cases *a* and *b*. Another interesting result is that in case *c*, the electricity shared across DESs from all CHPs is maximum in order to satisfy the community's user demand in the absence of grid power. Conversely, in case *d*, the electricity for self-use in each DES is maximum in order to satisfy the electricity demand of the corresponding user in the absence of grid power and energy shared from other DESs.

Fig. 6 shows the expected optimized operation strategies of the various DESs in the LEC for heat under the four operation modes. In case *a*, because of sharing of electricity and thermal energy across DESs and using of the grid power for heat pumps, the amount of self-used thermal energy in the LEC is lower than that found in the other three cases. In case *b*, when DESs do not share energy, the self-used thermal energy increases, resulting in a larger usage of thermal storage. When DESs operate in the islanded mode, heat pumps generate much less thermal energy for case *d* comparing with cases *a* and *b*, and case *c* has null thermal energy from heat pumps. This also explains the increase in the total expected daily energy cost. In fact, the heat pumps represent a convenient technology for economic purposes thanks to their high energy conversion efficiency. In case *d*, without energy sharing among DESs, the self-used thermal energy of the LEC is the largest among the four cases, since there is no possibility to use thermal energy from other DESs to satisfy the heat demand.

To analyze the amount of self-used and shared thermal energy, the total daily amount of thermal energy among the DESs and the end users under case *a* are reported in Table 3 below.

Table 2
Expected costs for the different DES operation modes in the winter day.

Case	Total expected net energy cost ($)	Expected energy cost ($)	Expected carbon Tax ($)	Expected revenue ($)
Case *a*	2037.26	2145.98	74.96	183.69
Case *b*	2078.14	2011.31	70.67	3.84
Case *c*	2285.42	2216.02	69.40	0.00
Case *d*	2333.91	2263.06	70.85	0.00

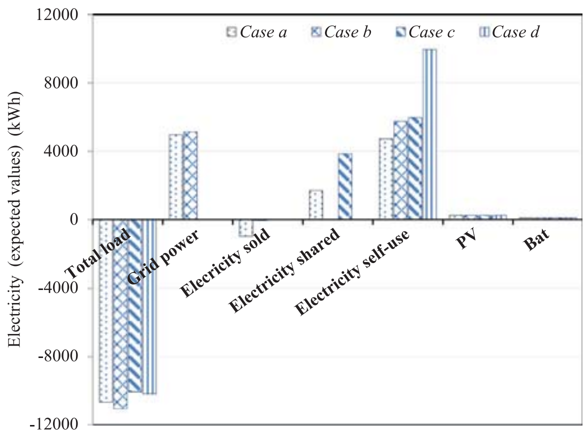


Fig. 5. Expected optimized operation strategies of the various DESs in the LEC for electricity under the four cases in the winter day.

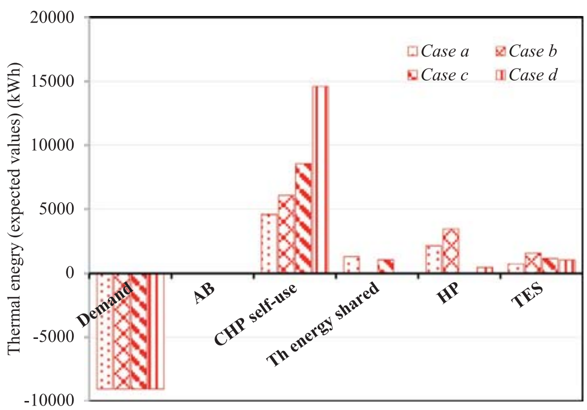


Fig. 6. Expected optimized operation strategies of the various DESs in the LEC for heat under the four cases in the winter day.

Table 3
Daily thermal energy shared among DESs and users for case a in the winter day (kWh).

From DES To User	DES1	DES2	DES3	DES4
Case a				
1. Supermarket	Self-use	2.8	139.87	**1061.79**
2. Strip mall	24.52	Self-use	828.16	2.69
3. Office building	75.56	33.64	Self-use	1.57
4. Mid-rise apartment	263.36	85.15	88.56	Self-use

For case *a*, the supermarket receives the largest share of thermal energy from all DESs in the LEC, as it has the largest thermal demand. Most of this thermal energy is made available by DES4 associated to the mid-rise apartment. This is due to the large usage of CHP for selling electricity back to the utility grid for increasing the associated revenues, with consequent large amount of thermal energy recovered to be shared. This allows to reduce the total expected net cost.

3.2.2. Optimization results for the LEC in the summer day

The expected values of the total net energy costs, with the various terms of the objective function are shown in Table 4 for the four cases in in the summer day.

Similar to what is found in the winter case, the lowest total expected energy cost is achieved in case *a*. In case *b*, the total expected net energy cost increases by 1.6% as compared to case *a*, and the revenue of selling electricity back to the grid decreases by 37.8%. For case *c*, the expected net energy cost increases by 14.0% as compared to case *a*. Similar to the winter day, case *d* presents the poorest performances among the four cases also in the summer day, with the total expected net cost increased by 15.3% as compared to case *a*.

To compare the four operation modes in the summer day, Fig. 7 shows the expected values of: (1) the total electrical load; (2) the total grid power bought from the utility grid; (3) the total electricity sold to the utility grid, kept for DES self-use and shared across DESs (from all CHPs); (4) the total electricity generated by all PV systems; and (5) the total electricity discharged by all batteries.

The operation strategies are similar to those presented for the winter case. For base case *a*, the electricity sold back to the utility grid is larger than that in case *b*. In these two cases, the total electrical load is almost the same, and the electricity provided from PVs and batteries is also the same. Also, the increase of usage of electricity bought from the utility grid is lower than the increase of the electricity generated by CHPs in case *a* comparing with case *b*. For cases *c* and *d* with DESs operating in the islanded mode, the total electrical load is lower than that found in cases *a* and *b* with DESs operating in the grid-connected mode, due to the lower usage of heat pumps for cooling purposes. In addition, case *d* has the largest self-used electricity. In fact, in this case, only CHPs are used to satisfy the electrical load beyond PV systems and batteries.

Fig. 8 shows the expected optimized operation strategies of the various DESs for cooling under the four cases in the summer day. It can be noted that, for case *b*, without sharing energy among DESs, the usage of heat pump for cooling purposes is the largest among the four cases. Instead, for cases *c* and *d* with DESs operating in the islanded mode, heat pumps generate much less thermal energy for cooling comparing to cases *a* and *b*. In addition, for case *d*, without energy shared across DESs, much more thermal energy from CHP is used to run the absorption chiller for cooling.

3.3. Expected optimized operation strategies of one DES

For the illustration purposes, the expected optimized operation strategies of the CHP in DES2 associated with the strip mall are discussed in the following in the winter and summer days considering the base case (case *a*), which shows the best economic and environmental performances.

3.3.1. Expected DES2 optimized operation strategies in the winter day

In the winter day, electricity balance, and the expected CHP optimized operation strategies of DES2 under case *a* are shown in Fig. 9a and b, respectively. Results for the other DESs in the LEC are similar.

As shown in Fig. 9a, the grid power is mainly used in hours characterized by low grid prices, e.g., from hours 1 to 12, and from hours 22 to 24. This operation strategy actually allows to reduce the energy cost in DES2. Instead, when the grid price is high as occurs from hours 13 to 21, the battery and the electricity collected from the other DESs in the LEC are used to satisfy the demand. In Fig. 9b, it can be seen that the power from the CHP is all self-used within the LEC, and there is no extra power sold back to the utility grid.

The heat energy balance is shown in Fig. 10. At hour 7, the thermal storage is charged by the CHP, and then the energy in the storage is used to meet the heat demand at peak hours. The heat pump powered by grid power is used from hours 7 to 12, in correspondence of low grid prices. Instead, for the rest of the day, the heat demand is completely met by the thermal energy collected from the other DESs in the LEC.

Table 4
Expected costs for the different DES operation modes in the summer day.

Case	Total expected net energy cost ($)	Expected energy cost ($)	Expected carbon Tax ($)	Expected revenue ($)
Case *a*	1047.58	1096.58	38.90	87.90
Case *b*	1064.10	1080.99	37.82	54.71
Case *c*	1194.01	1157.75	36.26	0
Case *d*	1207.93	1171.25	36.68	0

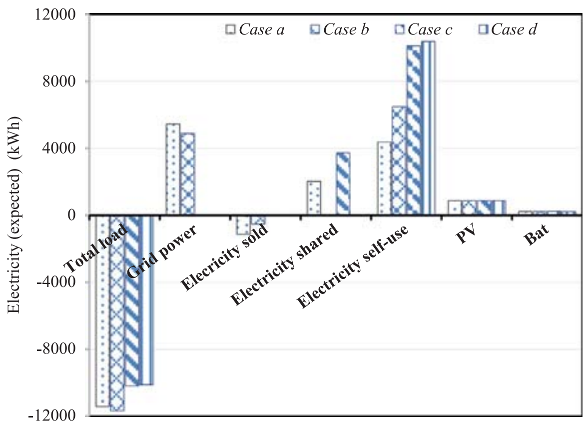


Fig. 7. Expected optimized operation strategies of the various DESs in the LEC for electricity under the four cases in the summer day.

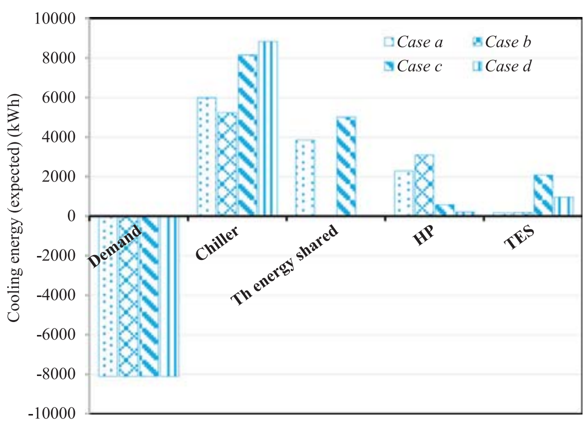


Fig. 8. Expected optimized operation strategies of the various DESs in the LEC for cooling under the four cases in the summer day.

This result is consistent with those reported in Table 3.

3.3.2. Expected DES2 optimized operation strategies in the summer day

For the summer day, electricity balance, and the expected CHP optimized operation strategies of DES2 under case *a* are shown in Fig. 11a and b, respectively. Results for other DESs in the LEC are similar.

As shown in Fig. 11a, similar to what occurs in the winter day, also

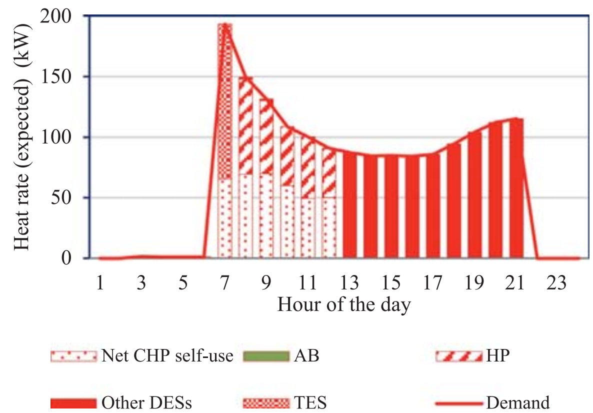


Fig. 10. Expected heat energy balance in DES2 in the winter day.

in the summer day, the grid power is mainly used when the grid price is low, namely from hours 1 to 12, and from hours 23 to 24. From hours 13 to 22 when the grid price is high, the demand is mostly satisfied by the PV, battery and electricity from other DESs in the LEC. In Fig. 11b, it can be seen that the power from the CHP is all self-used within the LEC, and there is no extra power sold back to the grid.

Finally, Fig. 12 shows the cooling energy balance in DES2. It can be seen that most of the demand is covered by the absorption chiller and heat pump. Only at hours 6 and 8, the demand is also covered by the thermal storage.

3.4. Comparison of deterministic and stochastic results

To demonstrate the benefits of considering uncertainties through the Markovian-based stochastic approach, the problem is also solved by using the deterministic approach for the winter and summer days, where the expected PV generation is considered. The total expected net energy costs, and the various terms of the objective function for the base case *a* obtained by using the stochastic and deterministic approaches in the winter and summer days are shown in Table 5 below.

For the winter day, the total expected net energy cost obtained by using the stochastic approach is reduced by 43.7% as compared with that found by using the deterministic approach as the uncertainties of PV power generation are better explored, and the expected energy cost and carbon tax are also reduced. For the summer day, the cost reduction on the total expected net energy cost is as much as 71.1%, as the PV power generation is higher in summer. These results highlight the benefits of the stochastic approach as compared with the deterministic

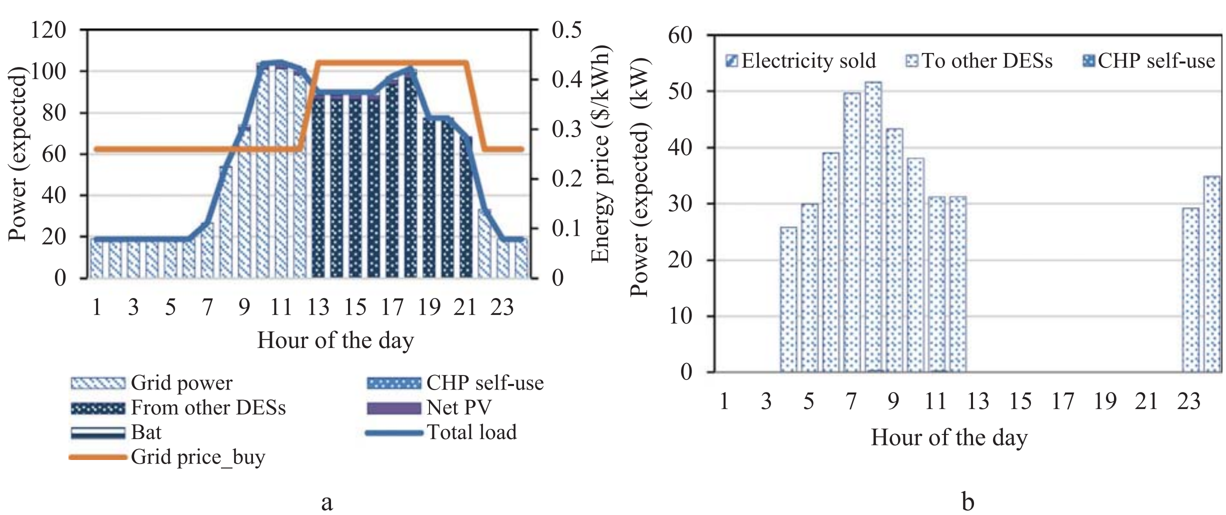
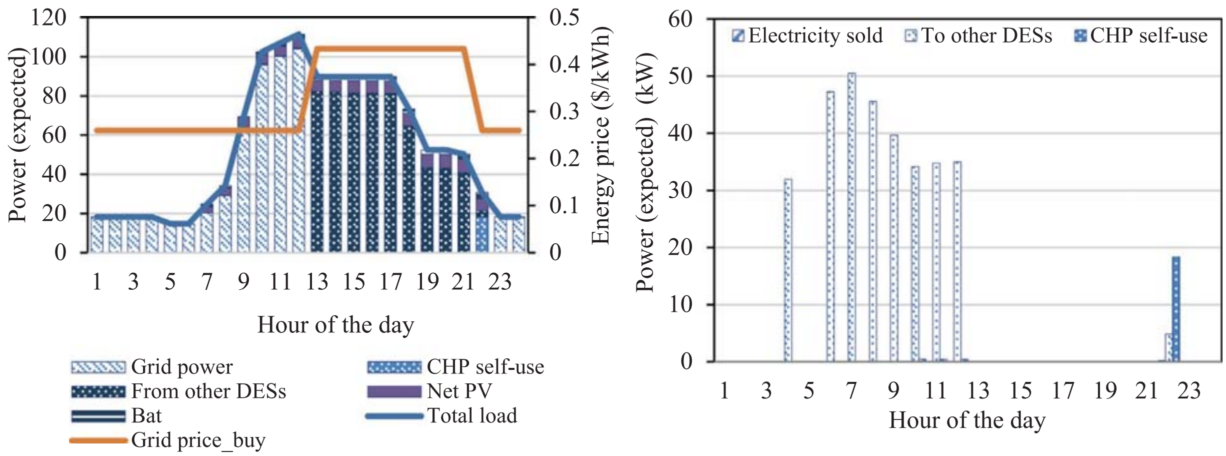


Fig. 9. (a) Expected electricity balance in DES2 in the winter day. (b) Expected CHP optimized operation strategies of DES2 for electricity in the winter day.



a b

Fig. 11. (a) Expected electricity balance in DES2 in the summer day. (b) Expected CHP optimized operation strategies of DES2 for electricity in the summer day.

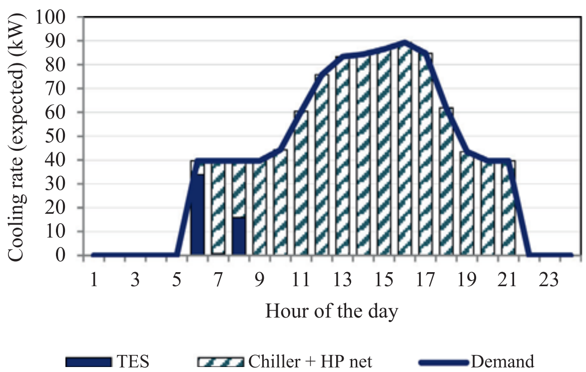


Fig. 12. Expected cooling energy balance in DES2 in the summer day.

one, and are consistent with those presented in [51], where comparison was made between the deterministic and stochastic approaches applied to a multi-objective optimization problem for the operation of a DES by considering economic and environmental objectives. It was found that the daily energy cost and CO_2 emissions obtained under the stochastic approach were lower than those obtained under the deterministic one at all points of the Pareto frontier.

To demonstrate the effectiveness of the Markovian-based stochastic approach, four more winter cases are considered by varying the load, with a load scale factor that is randomly generated for each hour, each load type, and each end-user. Four instances are created with load scale factors falling in: (a) [1, 1.1]; (b) [1, 1.2]; (c) [0.9, 1]; and (d) [0.8, 1]. The total expected net energy costs, and the various terms of the objective function for the base case *a* obtained by using the stochastic and deterministic approaches in the winter day are shown in Fig. 13 below.

With the same load scale factors, another four instances are created for the summer day. The results are presented in Fig. 14 below.

For the winter day, the total expected net energy costs obtained by using the stochastic approach are reduced by 44.7% - 45.3% as compared with those found by using the deterministic approach, and the expected energy cost and carbon tax are also reduced. For the summer day, the cost reduction on the total expected net energy cost is much higher in the range 70.0% - 70.6%. These results highlight the effectiveness of performance of the Markovian-based stochastic approach.

In terms of computational efficiency, it takes 5 to 8 seconds to solve the problem by using the stochastic approach, while it takes about 1 second by using the deterministic one. When the number of PV states increases, the computational time may increase correspondingly.

4. Conclusions

An LEC refers to a set of energy users deciding to make common choices in terms of satisfying their energy needs, in order to maximize the benefits deriving from this collegial approach, thanks to the implementation of a variety of electricity and heat technologies and energy storage and the optimized management of energy flows. An LEC may consist of multiple DESs interconnected through local grid and heating network to satisfy multi-energy demand of the community's users. The contribution of this paper is to present a mathematical model for day-ahead operation optimization of multiple DESs with renewables in an LEC and a Markovian-based stochastic approach is proposed to take into account renewables uncertainties. The problem is to decide the operation strategies of energy devices in each DES, as well as the amount of electrical and thermal energy shared across DESs with the aim to minimize the expected net daily energy cost and CO_2 emission cost, while also satisfying the community multi-energy demand. A stochastic mixed-integer linear programming model is established with uncertain PV generation modeled by a Markovian process to avoid the difficulties and drawbacks associated with scenario-based methods. The problem is solved by using branch-and-cut. One of the strength points of the proposed optimization framework is scalability and flexibility for coordination of an arbitrary number of DESs and adaptation to a number of real contexts thanks to the wide variety of generation, conversion and storage technologies considered and the general mathematical formulation established. To show the effectiveness of the optimization model and the solution methodology, an LEC located in U.S. consisting of four DESs associated to buildings belonging to

Table 5
Daily costs obtained with the deterministic and stochastic (expected cost) approaches for the winter and summer cases.

Day	Approach	Total (expected) net energy cost ($)	(Expected) Energy cost ($)	(Expected) Carbon tax ($)	(Expected) Revenue ($)
Winter	Stochastic	2053.98	2053.15	72.17	71.34
	Deterministic	3623.37	3816.93	131.76	325.32
Summer	Stochastic	1056.73	1054.41	37.51	35.19
	Deterministic	3627.13	3908.23	136.22	417.32

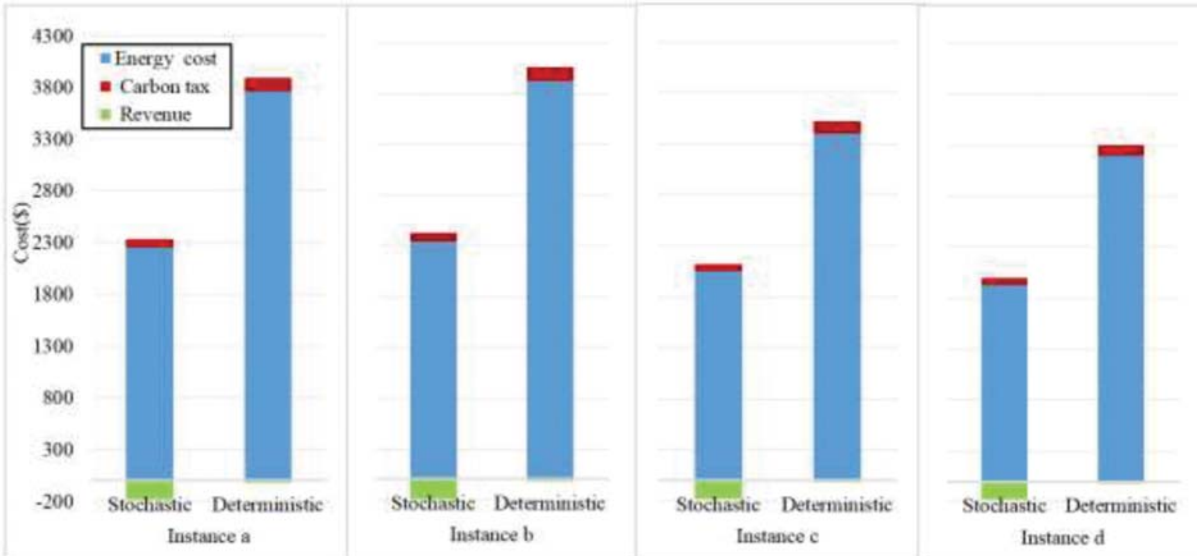


Fig. 13. Optimization results obtained with the deterministic and stochastic (expected values) approaches for four random generated cases in the winter day.

commercial and residential sectors is considered in the case study. Numerical results demonstrate that the method proposed is efficient to guarantee the economic and environmental sustainability of the LEC. Indeed, both in the winter and summer cases analyzed, the total expected net energy cost of the LEC is reduced through the integrated management of the interconnected DESs. In detail, by comparing different DES operation modes in the LEC, it is found that the interconnected DESs operating in grid-connected mode have the best economic and environmental performances among the four operation modes, showing the lowest expected net energy cost as compared with the other cases. Conversely, the DESs operated without sharing energy and in islanded mode show the poorest performances with cost increase of 14.6%-15.3% as compared with the best case. What is more, the results highlight that, through exploring uncertainties of PV generation, the stochastic approach is more efficient than the deterministic one to optimize economic and environmental performances of the LEC. In the winter and summer cases analyzed, the total expected net energy cost obtained by using the stochastic approach is reduced by 43.7-71.1% as compared with those found through the deterministic approach, since the energy cost and carbon tax reduce. The results demonstrate the potential benefits that can be achieved in LEC through the optimized and integrated management of local energy resources aiming to foster efficient use of the available energy. The eight testing instances with randomly generated load scale factors also demonstrate the effectiveness and computational efficiency of the approach. In future work, the peer-to-peer energy trading, as a key aspect in the energy sharing of LECs, will be investigated through the modeling of the features of local trading in a local electricity market.

CRediT authorship contribution statement

Bing Yan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing. **Marialaura Di Somma:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Giorgio Graditi:** Writing - original draft, Writing - review & editing, Visualization, Supervision. **Peter B. Luh:** Writing - original draft, Writing - review & editing, Visualization,

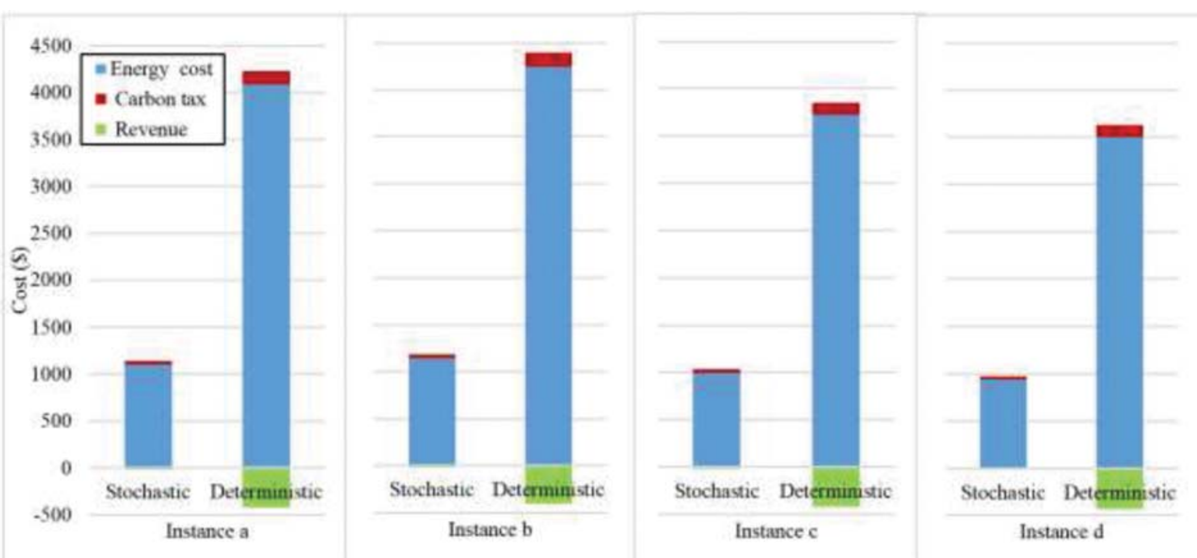


Fig. 14. Optimization results obtained with the deterministic and stochastic (expected values) approaches for four random generated cases in the summer day.

Supervision.

Declaration of Competing Interest

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

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