Risk-based Peer-to-peer Energy Trading with Info-Gap Approach in the Presence of Electric Vehicles

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Abstract **–** Small-scale smart microgrid is prone to economic consideration of adequate transactive energy sharing and reliable certified power pool hub. Moreover, direct integration of efficient with renewable energy providers in presence of storage such as electric vehicle (EV) aggregation improves the performance of energy systems and guarantees secure trade among the consumers. However, unified modeling of the energy community framework faces the challenge of load management. In this paper, an optimal risk management procedure is proposed for renewable-based presumes such as photovoltaic (PV), and EV to maximize the horizon of uncertainty parameter. The energy demand in peer to peer (P2P) household energy sharing is considered as the uncertain parameter. To this end, in order to study the behavior of a risk-averse and a risk-seeker decision-maker, an information-gap decision theory (IGDT) probability model is applied. In order to demonstrate the performance of the proposed approach, the model is implemented in a test microgrid and the simulation results are presented and discussed.

Keywords **–** Peer to peer (P2P) trading, risk management, electric vehicle (EV), information gap decision theory (IGDT).

Nomenclature

H	The number of complexes
T	The horizon for scheduling
λ_t^G	The cost of importing electricity from the grid upstream
$P_{t,h}^G$	Imported from the upstream grid.
$P_{t,h}^L$	Each complex's load
$P_{t,h}^{G,L}$	The imported power from the upstream network to satisfy each complex's demand
$P_{t,h}^{P2P,L}$	The quantity of electricity exchanged between complexes

$P_{t,h}^{Dch,L}$	The EVPL's discharge power
$P_{t,h}^{PV,L}$	The solar panel's generated electricity
$P_{t,h}^{G}$	The overall quantity of power imported from the upstream network
$P_{t,h}^{G,L}$	The upstream grid's exported power to satisfy each complex demand
$P_{t,h}^{G,Ch}$	The upstream grid's exported energy used to charge EVs parked at the EVPL
$P_{t,h}^{PV}$	The total power produced by the PV unit
$P_{t,h}^{PV,L}$	Each complex is supplied with imported power from a PV system
$P_{t,h}^{PV,P2P}$	The PV unit's produced energy used for peer-to-peer trading
$P_{t,h}^{PV,Ch}$	The PV unit's generated power used to charge the EVs parked at the EVPL
$P_{t,h}^{Ch}$	The total power stored in the batteries of EVs that are parked in the EVPL
$P_{t,h}^{P2P,Ch}$	The P2P trading power for charging the EV's parked in the EVPL
$P_{t,h}^{Dch}$	The total amount of discharging power of EVs' battery
$P_{t,h}^{Dch,L}$	The amount of EV battery discharging power required to meet each complex's demand
$P_{t,h}^{Dch,P2P}$	The amount of the EV battery's discharge power for P2P trade
$SOC_{t,h}$	The stored energy level at the current time interval
η^{G2V} , η^{V2G}	The EVPL's charging and discharging efficiency
N_h^{EV}	The number of EVs that are parked in the EVPL
P_{Max}^{Ch} , P_{Max}^{Dch}	EVPL's maximum charge and discharge limits
$\alpha_{t,h}^{Ch}$, $\alpha_{t,h}^{Dch}$	The auxiliary variables employed to indicate the operation mode of EVPL
$Z_{t,h}$	A parameter to indicate the availability of EVs in the EVPL
ΔSOC^{EV}	The different SOC of EV between two consecutive hours
Δ_{SOC}^{Max}	The maximum SOC difference limitation between two consecutive hours

$P_{t,h}^{P2P,In}$	Each complex's total input power
$P_{t,h}^{P2P,O}$	The total amount of each complex output
K	A big number
$\mu_{t,h}^{P2P,In}$	An auxiliary binary variable
α	The boundary of uncertainty
C_r	Referred to as the microgrid's critical cost
C_0	The deterministic value of the optimum cost of the microgrid
C_p	Defined as the target cost of the microgrid

1. Introduction

Nowadays, due to the concerns about air pollution, which is mainly caused by fossil fuel power plants, most consumers have decided to supply their demands by distributed energy resources to be self-sufficient and have clean air. However, in some circumstances, the output power of prosumers is more than their requirement. On the other hand, due to several reasons, such as lack of access to battery storage or insufficient storage capacity, the generated power inevitably could be wasted by distributed energy resources. Recently, implementing a peer-to-peer (P2P) trading method has partially solved this problem by selling extra generated power of houses to the houses, requiring more energy (Suthar et al., 2023). The significance of P2P energy trading method is demonstrated in (Espadinha et al., 2023) where a P2P optimization model was created to evaluate the P2P role for decarbonizing Portugal by 2050. In this study, it is assumed that each of the 278 considered municipalities should create an energy community with four competitive sectors as players.

At the Portuguese national level, expenses and CO2 emissions decreased under the communal self-consumption and P2P scenarios, respectively. Moreover, the services sector emerged as an active

trader, with the biggest volume of energy sold on the P2P market, while the residential sector clearly displayed buyer and seller behavior.

Through employing this method, several goals can be achieved. For instance, surplus generated power would not waste and the homeowner; who has surplus generated power; can gain economic benefit by selling it to other consumers. To recapitulate, this indicates the effectiveness of the proposed method and decreases the dependency of microgrids from the upstream network as much as possible (Soto et al., 2021; Tushar et al., 2021).

In this part, a review of recent works and research activities on P2P energy trading is presented. A novel P2P market structure based on a multi-bilateral economic dispatch (MBED) is presented in (Sorin et al., 2019), where the relaxed consensus+innovation (RCI) approach is utilized to solve the studied problem. By implementing this method, social welfare is maximized besides considering consumer performance. Likewise, in (Tushar et al., 2019), a motivational game-theoretic approach is employed for P2P energy trading in a smart grid to reach some targets such as the reduction of carbon emissions and the energy cost, encouraging the users for participating in the energy trading. To help the centralized power system to decrease the total electricity demand of customers at the peak hour, a P2P energy trading scheme is implemented by formulating the cooperative Stackelberg game in (Tushar et al., 2020). Authors in (Siano et al., 2019) have studied the concept of energy as a new consensus protocol for P2P energy exchange management. In order to decrease the power peaks in critical time periods, a subscription-based tariff structure is presented in (Almenning et al., 2019). A prediction-integration trading optimization model for prosumers in the continuous double auction-based electricity market is implemented in (Chen et al., 2019) to improve the prosumer profit in different market situations and increase the market

transaction rate. In another study, for solving the energy-sharing problem, a two-stage energy-sharing strategy is developed to result in economic benefits in energy buildings (Cui et al., 2019). In (Hahnel et al., 2020), Huhnel et al have focused on customer preferences in P2P energy trading. They have tried to make the extent homeowners more clear regarding their behavior as well as their conditions in the P2P energy trading system. The main aim of this study is to enhance the amount of P2P trading in decentralized energy systems. According to their analysis of German homeowners, it is shown that the main factors of homeowners' trading behavior are the state of charge of private storage units and the electricity prices of the community. In order to achieve the benefits as well as decrease the need for sensing and communication infrastructures in P2P energy sharing, a two-stage control method is applied in (Long et al., 2018). In this work, each prosumer is allowed to control its distributed energy resources through a third-party entity. Besides that, the authors in (Melendez et al., 2019) have proposed a new method to investigate the improvement of the end-user consumers from aggregation and develop some rules in order to minimize the cost of the system. To survey the feasibility of renewable sources like PV systems in P2P energy trading and evaluate the economic benefit, an optimization model is applied in (Nguyen et al., 2018). Valuable good guidelines and a review of some recent works about the real blockchain-based electricity market are studied in (Wörner et al., 2019). In (Talari et al., 2022), a fully decentralized market mechanism is proposed that respects prosumers' preferences, including their readiness to trade renewable energy, the reputation of their trading partners, and their position within the network. Powerful consumers are encouraged to participate in the market on their own while maintaining their privacy.

Both uncertainty trading and energy trading are considered in the P2P local electricity market model in (Zhang et al., 2020). In order to increase participation in the reserve market, ref.

(Bjarghov et al., 2019) have proposed a three-stage stochastic market-clearing model, where real-time markets, and internal intraday are cleared properly considering the uncertainty of load and activation of reserves. The employment of game-theoretic approaches for P2P energy trading is studied and various games and auction theoretic approaches are proposed for providing information about the systematic classification in (Tushar et al., 2018). The authors of (Zepter et al., 2019) have studied integrating prosumer communities into the existing day-ahead and intraday markets, where a stochastic programming approach was developed in two levels to enhance the economic performance of the P2P trade and battery storage.

The integration of P2P energy sharing with demand-side management was put forth in (Zhao et al., 2023) for energy management. In order to guarantee that every household could fairly participate in P2P sharing and take advantage of cheap PV electricity, it adopted a uniform price and energy allocation method based on the ratio of supply to demand. A multi-objective optimization strategy was utilized to find the scheduling scheme for flexible loads when community members engage in P2P sharing. On the structure of this model, the uncertainty and the employment of EV is disregarded.

The authors in (Xia et al., 2023) proposed a P2P energy trading mechanism that included a preference marginal price and an uncertainty local marginal price (LMP). Although this paper considers the uncertainty of the renewable energy recourses at the first step, it does not consider the load uncertainty. In (Haider et al., 2022), a centralized optimization algorithm is used in P2P energy trading procedure, which is encouraged by pricing factors considering EV charging and discharging behaviors. In this paper, EVs have been considered but there is not any renewable energy resource and the existing uncertainties have not been taken into account.

According to (Hutty et al., 2021), a local microgrid of 50 households with penetrations of PV and EV has been modeled by a P2P energy trading platform. The authors in this work employed the P2P concept with unidirectional EV chargers and chargers that can discharge EV battery energy to the home or the grid; the usage of energy storage has been taken into consideration. However, the uncertainty of the consumers' load is not managed in this work which can affect the strategy of the decision-maker.

A P2P energy trading platform for prosumers has been introduced as a generalized aggregative game in (Belgioioso et al., 2022), where a network operator is in charge of enforcing the system's operating limitations. A distributed market-clearing mechanism has been employed in this paper. However, in the designation of this model, there are not any EVs, PVs, and uncertainty.

In (Yang et al., 2022), a Stackelberg game model was used to account for the interaction between the prosumers trading energy in a P2P market and the grid operator. On the prosumer side, distributed renewable generators and energy storage technologies are taken into account. The bi-level optimization issue generated by the Stackelberg game has been transformed into a single-level mixed-integer quadratic programming (MIQP) by examining the problem structures in order to address the difficulties of finding the network fee price. The difference of this paper with our research is that the authors did not consider EVs and also the uncertainty of the load has been ignored.

Network-constrained P2P energy trading scheme for multiple microgrids under uncertainty has been addressed in (Liu et al., 2023). A bi-level optimization framework has been presented to make a connection between the P2P transactions under uncertainty and physical power flows monitored by distribution system operators. To reduce power losses and ensure the operational security of local distribution networks, an upper-level conditional optimum power flow model is developed.

A stochastic programming-based P2P trading model for multiple microgrids is developed at a lower level. A nested bi-level distributed algorithm with a parallel analytical target cascading algorithm and an alternating direction multiplier method are created to solve the model in a distributed manner while realizing the consistency of decision-making processes between the two levels and among various microgrids. The authors in this paper do not consider any renewable energy resources that can enhance the flexibility of the P2P energy trading framework.

In (Fernandez et al., 2021), an energy management system for a community is assumed that enables P2P energy trading between customers with renewable energy units, a central storage facility, and a power grid. Two optimization frameworks for distributing extra on-site generated energy are established. Whereas in the first framework, a game theoretical model, maximizes consumer utilization at the lower level and the revenue of the common storage facility at the higher level, the second framework maximizes the combined revenue of sellers and purchasers. The difference of this paper with our paper is that not only EVs but also the load's uncertainty has been neglected.

According to the studied literature review, it can be observed that the P2P energy trading scheme is beneficial to the power system but appears to be challenging at the same time. In P2P transactions, purchasers are expected to trade their required demand independently and directly from the peer suppliers, which imposes a notable amount of uncertainty into the P2P energy trading platform. Therefore, encouraging the prosumers and consumers to participate in such an environment with significant uncertainty in the amount of the traded demand is a challenging task. Therefore, the model of energy transactions in a P2P manner should be considered in handle of these challenges to manage the risk associated with the amount of consumer consumption is necessary, while minimizing the cost of the whole P2P energy trading platform. The uncertainty

in the P2P energy trading platforms is one of the most critical issues; especially the uncertainty originating from the amount of the load of the end-users; that should be taken into account which are neglected in (Belgioioso et al., 2022; Fernandez et al., 2021; Zhao et al., 2023). Moreover, the employment of EVs in the energy system can provide more flexibility to the end-users to participate in the P2P transactions which are not given proper attention or are neglected totally in (Belgioioso et al., 2022; Fernandez et al., 2021; Yang et al., 2022).

A taxonomy table is presented to compare a number of the recent models with the proposed framework. It should be noted that there are a few models that considered the uncertainty in the management of the P2P frameworks; however, no efficient strategy is provided for managing the system operation against the demand uncertainty. As the cost of the framework could be reduced if an accurate risk-management model for handling the uncertainty posed by the demand of the participants is chosen. In fact, in order to take appropriate actions against this kind of uncertainty, optimal operating strategies are required to be provided. Moreover, analyzing the source of uncertainty in the P2P framework from different perspectives is also another key point that provides beter viewpoint to the decision-maker to choose the best strategy against the demand uncertainty.

Table 1: A taxonomy table comparing a number of P2P energy trading platforms.

Ref.	Clean production		Uncertainty	Risk management from different perspectives	Objective
	EV	PV			
(Zhao et al., 2023)	×	✓	×	×	Minimizing the overall cost of the community
(Haider et al., 2022)	✓	×	×	×	Reducing network congestion
(Belgioioso et al., 2022)	×	×	×	×	Maximizing the safety and reliable operation of the system
(Yang et al., 2022)	×	✓	×	×	Maximizing the economy benefits.
(Liu et al., 2023)	×	×	✓	×	Minimizing power losses and guaranteeing the operating security of local distribution networks.

(Fernandez et al., 2021)	×	✓	×	×	Maximizing consumer utilization at the lower level and the revenue of the common storage facility at the higher level.
(Hutty et al., 2021)	✓	✓	×	×	Maximizing the penetration of PVs and EVs
(Xia et al., 2023)	×	✓	✓	×	Minimizing the operation cost
Our model	✓	✓	✓	✓	IGDT-based risk-constrained models corresponding to the demand uncertainty are formulated in the robust and opportunistic structures

In order to resolve the issues expressed in the studied literature review, this paper develops an Information gap decision theory (IGDT) based optimization framework for studying the performance of a local operator in a microgrid connected to the main network under demand uncertainty. Using the IGDT, this model was precisely formulated to address both robust and opportunistic behaviors in dealing with uncertainties. The obtained results from this approach can be used by the local operator to apply the appropriate operating strategies within various uncertainty levels. Different aspects of demand uncertainty are taken into account in the IGDT method and then according to the desired targets for the risk-averse and risk-seeker decisions, the provided strategies are applied to determine the best possible configurations for the local operator under different uncertainty levels.

The rest of the paper is organized as follows: Section 2 is dedicated to the problem formulation. The Uncertainties are discussed in Section 3. The results and required input data are presented in Section 4. Finally, the conclusions of this paper are provided in Section 5.

2. Problem formulation and constraints

In this section, the mathematical formulation associated with P2P energy trading in a renewable grid-connected microgrid system is presented. In order to explain the decision variables in the proposed model, a schematic of the framework is depicted in Fig. 1. According to Figure 1, the

192 studied system represents an energy framework interconnected with the upstream power grid,
193 enabling a bidirectional flow of electric power. Additionally, two prosumers involved in the system
194 possess the capability to engage in P2P energy trading, which further empowers the system's
195 energy flexibility. Each prosumer is equipped with an EV parking lot and renewable energy
196 resources, i.e. PV solar panels. The primary function of the prosumers in this system is to fulfill
197 the power requirements of their own demand through the upstream grid, the PV panels, and the
198 EV parking lot. During certain hours, if the prosumers have surplus power that is not required,
199 they have the option to engage in P2P energy transactions with another peer. Alternatively, they
200 can choose to sell their excess power to the upstream network. Moreover, the EVs within the
201 system also possess the ability to engage in a bidirectional power exchange. This energy-sharing
202 mechanism optimizes the utilization of available resources and enhances the overall energy
203 efficiency of the system. The employed decision variables shown in this figure are explained and
204 discussed in detail.

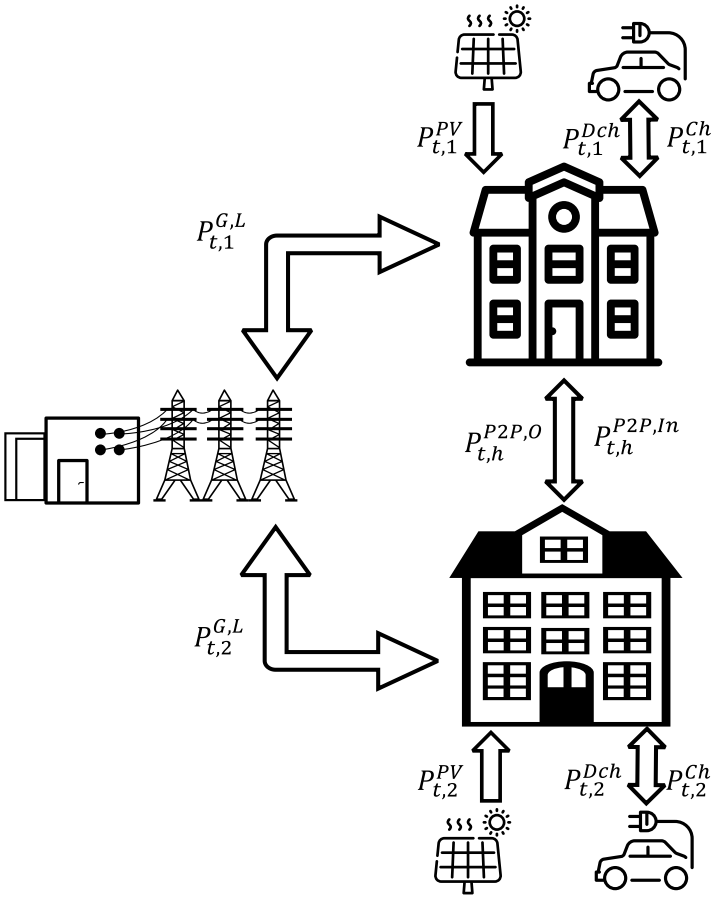


Fig. 1. The schematic of the proposed P2P framework.

2.1. Objective function

As the objective function, the total cost of the system including the cost of power purchase from upstream grid, should be minimized (1).

$$Obj = Min \sum_{t=1}^{T} \sum_{h=1}^{H} P_{t,h,}^{G} \lambda_t^G \quad (1)$$

where: *Obj* is the objective function, H is the number of complexes, h is the complex index, T is the scheduling horizon, t is the time index,$P_{t,h}^{G}$ is imported power from the upstream network, λ_t^G is the price of power imported from the upstream grid.

2.2. Energy balance constraint

According to the power balance constraint in the studied system (2), the energy demand should be met with the traded energy, grid power, generated power by renewables and the charge/discharge of EVPL.

$$P_{t,h,s}^{L} = P_{t,h}^{G,L} + P_{t,h}^{P2P,L} + P_{t,h}^{Dch,L} + P_{t,h,s}^{PV,L} \qquad \forall t, \forall h \tag{2}$$

where: $P_{t,h}^{L}$ is the load of each complex, $P_{t,h}^{G,L}$ is the imported power from the upstream network for meeting the demanded power of each complex, $P_{t,h}^{P2P,L}$ is the trading power between complexes, $P_{t,h}^{Dch,L}$ is the discharge power of EVPL, $P_{t,h}^{PV,L}$ is the generated power of the PV unit, respectively.

2.3.Generation Supply

To meet the energy demand, each complex supply power from the upstream network, PV unit and EVPL.

2.3.1. Power Grid

Energy is purchased from the upstream network to supply energy demand in each complex and charge the EVs parked in the EVPL, as expressed (3).

$$P_{t,h}^{G} = P_{t,h}^{G,L} + P_{t,h}^{G,Ch} \qquad \forall t, \forall h \tag{3}$$

where $P_{t,h}^{G}$ is the total amount of imported power from the upstream network, $P_{t,h}^{G,L}$ is the exported power from the upstream grid to meet each complex demand, $P_{t,h}^{G,Ch}$ and is the exported power from the upstream grid to charge EVs parked in the EVPL.

2.3.2. Photovoltaic (PV) units

Generated power of PV is used for supplying each complex demand, P2P trading, and charging the EVs parked in the EVPL, as expressed in (4).

$$P_{t,h,s}^{PV} = P_{t,h,s}^{PV,L} + P_{t,h,s}^{PV,P2P} + P_{t,h,s}^{PV,Ch} \qquad \forall t, \forall h \tag{4}$$

where $P_{t,h,s}^{PV}$ is the total amount of generated power of PV unit in time *t*, complex *h* and scenario *s*, $P_{t,h,s}^{PV,L}$ is the imported power from PV system to each complex, $P_{t,h,s}^{PV,P2P}$ is the generated power of PV unit for P2P trading and $P_{t,h,s}^{PV,Ch}$ is the generated power of PV unit for charging the EVs parked in the EVPL.

2.3.3. Electric Vehicle Parking Lots

The equations (5)-(6) present the charging and discharging power of the EVs parked in the EVPL. In (5) the battery of parked EVs in the EVPL is charged by upstream network, traded P2P energy and PV unit.

$$P_{t,h}^{Ch} = P_{t,h}^{G,Ch} + P_{t,h}^{P2P,Ch} + P_{t,h}^{PV,Ch} \qquad \forall t, \forall h \tag{5}$$

where $P_{t,h}^{Ch}$ is the total amount of power in the battery of p EVs parked in the EVPL, $P_{t,h}^{P2P,Ch}$ is the P2P trading power for charging the EV's parked in the EVPL. The battery of parked EVs in the EVPL is discharged for meeting the load demand of each complex and P2P trading (6).

$$P_{t,h}^{Dch} = P_{t,h}^{Dch,L} + P_{t,h}^{Dch,P2P} \qquad \forall t, \forall h \tag{6}$$

where $P_{t,h}^{Dch}$ is the total amount of discharging power of EVs' battery, $P_{t,h}^{Dch,L}$ is the discharging power of EVs' battery to meet the load demand of each complex, $P_{t,h}^{Dch,P2P}$ is the discharging power of EVs' battery for P2P trading.

2.4. Operation of Electric Vehicle Parking Lot

The operation of EVPL is modeled according to (7)-(13). The state of charge (SOC) of EVPL is expressed in (7), where the SOC at each time is dependent on the SOC at previous hour and the charge/discharge power.

$$SOC_{t,h} = SOC_{(t-1)h} + \left(P_{t,h}^{EVP,Ch} \eta^{G2V} - \frac{P_{t,h}^{EVP,DCh}}{\eta^{V2G}} \right) N_h^{EV} \qquad \forall (t > 1), \forall h \tag{7}$$

In the above constraint, $SOC_{t,h}$ is the stored energy level at the current time interval, η^{G2V} and η^{V2G} are the charging and discharging efficiencies of the EVPL and N_h^{EV} is the number of parked EVs in the EVPL.

$$SOC_{t,h} = SOC^{ini} + \left(P_{t,h}^{EVP,Ch} \eta^{G2V} - \frac{P_{t,h}^{EVP,Dch}}{\eta^{V2G}} \right) N_h^{EV} \qquad \forall (t=1), \forall h \tag{8}$$

According to (9), the energy stored in the battery of parked EVs in the EVPL must be within the technically specified capacity of EVPL.

$$SOC_h^{min} \le SOC_{t,h} \le SOC_h^{max} \qquad \forall t, \forall h \tag{9}$$

The SOC of EVs in the EVPL at the departure time should satisfy the desired SOC for each EV, as expressed in (10).

$$SOC_{t,h} \ge SOC_h^{Des} \qquad \forall t = Dep \tag{10}$$

The charging/discharging power constraints of EVPL are expressed in (11)-(12).

$$P_{t,ch}^{Ch} \le P_{Max}^{Ch} \alpha_{t,h}^{Ch} Z_{t,h} \qquad \forall t, \forall h \tag{11}$$

$$P_{t,ch}^{Dch} \le P_{Max}^{Dch} \alpha_{t,h}^{Dch} Z_{t,h} \qquad \forall t, \forall h \tag{12}$$

where P_{Max}^{Ch} and P_{Max}^{Dch} are the maximum charge and discharge limitations of EVPL, $\alpha_{t,h}^{Ch}$ and $\alpha_{t,h}^{Dch}$ are the auxiliary variables employed to indicate the operation mode of EVPL, $Z_{t,h}$ is a parameter to indicate the availability of EVs in the EVPL. It should be also noted that of electric vehicle parking lots (EVPL) cannot be charged and discharged operationally at the same time, as presented in constraint (13).

$$\alpha_{t,h}^{Ch} + \alpha_{t,h}^{Dch} \le Z_{t,h} \qquad \forall t, \forall h \tag{13}$$

The ΔSOC^{EV} is the different SOC of EV between two consecutive hours, which is limited in (14). Note that Δ_{SOC}^{Max} is the maximum SOC difference limitation between two consecutive hours.

$$-\Delta_{SOC}^{Max} \le SOC_{t,h} - SOC_{(t-1),h} \le \Delta_{SOC}^{Max} \qquad \forall (t>1), \forall h \tag{14}$$

2.5. Peer-to-peer (P2P) energy trading

The traded power between the complexes is expressed in (15)-(23). According to these constraints, received/delivered power by each complex is a combination of shared/received powers by other complexes.

Each complex trades with other complexes as a definition of P2P trading to meet its demand and charge the batteries of parked EVs in the EVPL, as expressed in (15).

$$P_{t,h}^{P2P,In} = P_{t,h}^{P2P,Ch} + P_{t,h}^{P2P,L} \qquad \forall t, \forall h \tag{15}$$

where $P_{t,h}^{P2P,In}$ is the total amount of input power of each complex. According to the equation (16), the output of each complex depends on the amount of discharging the EVs' battery and the amount of power generation of PV unit.

$$P_{t,h}^{P2P,O} = P_{t,h}^{Dch,P2P} + P_{t,h}^{PV,P2P} \qquad \forall t, \forall h \tag{16}$$

Where: $P_{t,h}^{P2P,O}$ is the total amount of each complex output. The output power of each complex is equal to the input power of other complexes in the P2P trading, as expressed in (17)-(18).

$$P_{t,h=1}^{P2P,In} = P_{t,h=2}^{P2P,O} \qquad \forall t \tag{17}$$

$$P_{t,h=1}^{P2P,O} = P_{t,h=2}^{P2P,In} \quad \forall t \tag{18}$$

The total amount of trading power in the P2P trading of each complex should be equal with other complexes at the end of the day, as expressed in (19).

$$\sum_{t=1}^{T} P_{t,h}^{P2P,In} = \sum_{t=1}^{T} P_{t,h}^{P2P,O} \qquad \forall h \tag{19}$$

Simultaneous import and export of energy via P2P energy trading is limited (20)-(21).

$$P_{t,h}^{P2P,In} \leq K\mu_{t,h}^{P2P,In} \qquad \forall t, \forall h \tag{20}$$

$$P_{t,h}^{P2P,O} = K\left(1 - \mu_{t,h}^{P2P,In}\right) \qquad \forall t, \forall h \tag{21}$$

where: K is a big number and $\mu_{t,h}^{P2P,In}$ is an auxiliary binary variable to avoid import and export power among complexes in P2P trading simultaneously.

3. Uncertainty modeling

Most of the time, due to endless uncertainties and lack of access to needed information by operators, they are unable to plan the operation of power systems for the future properly and accurately. To solve this problem, the authors decided to make an almost accurate prediction for the future by modeling these uncertainties with different methods. One of these uncertainties is the output power of solar cells because this parameter is mainly dependent on environmental conditions, and these conditions are constantly changing. In this paper, for modeling the output power of PV, series of scenarios based on the historical data are generated. And, to model another of the uncertainty that is the injected load of complexes from the network in the exciting microgrid as well as the electricity price for the energy purchased from the upstream grid, the IGDT is used to investigate a variety of cases from worst to best for reaching proper strategy.

IGDT is a decision-making framework that takes into account the impact of uncertainty on a system. It provides a way to model and analyze decision problems in the presence of incomplete or limited information. Figure 2 is depicted to address this concept in detail. In this figure, which represents a lift diagram, the different levels of the lift correspond to the different approaches taken to address uncertainty. When the lift is on the 0 floor, it signifies that the impact of uncertainty is neglected. Thus, we are in the deterministic mode. At this level, it is assumed that there are no uncertain parameters affecting the decision-making process. In other words, the decision-maker assumes that they have complete information and can accurately assess the outcomes and risks associated with their choices.

However, as the lift moves to higher levels, it indicates that the decision-maker acknowledges the existence of uncertainty and incorporates it into their decision-making process. Therefore, the opportunity function of IGDT method is used to evaluate the potential benefits that can be derived from uncertainty. Being on higher levels implies that the decision-maker is willing to take risks and seeks to exploit the uncertainty for possible gains. On the other hand, when the lift descends to levels below 0, it signifies that the robust function of IGDT is being employed. The robust function models the negative impacts of uncertainty, and the decision-maker aims to make their model resistant against these negative effects. By being on lower levels, the decision-maker demonstrates risk aversion and prioritizes safeguarding their system against the potential negative effects of uncertainty. Hence, the levels of the lift in Figure 2 represent the different attitudes of the decision-maker towards uncertainty. Higher levels indicate a risk-seeking behavior, where uncertainty is seen as an opportunity for potential benefits. Conversely, lower levels indicate risk-averse behavior, where the decision-maker focuses on protecting the system from the negative impacts of uncertainty through the application of the robustness function of the IGDT approach.

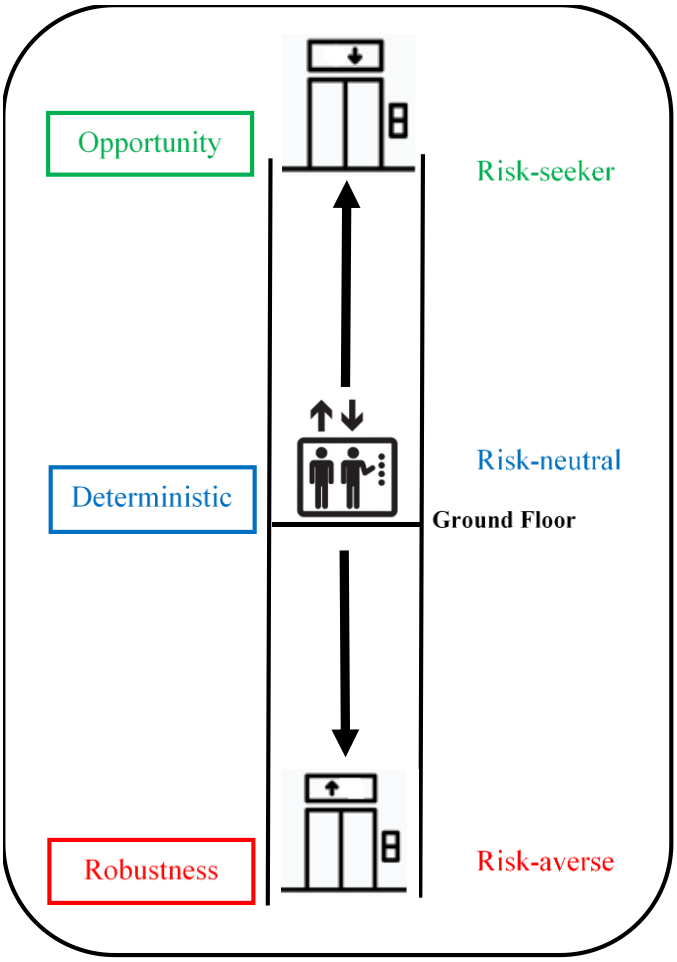


Fig. 2. The concept of the robustness and opportunity functions of information-gap approach

3.1. Robustness function of IGDT based method:

A risk-averse decision-maker uses the robustness function of the IGDT framework in order to find the maximum horizon of the uncertainty of the uncertain parameters which are the electricity price and load. This function is formulated as follows:

$$\hat{\alpha}(q, C_r) = Maximize\ \alpha \tag{22}$$

s.t:

$$C^* = Max\left(\sum_{t=1}^{T}\sum_{h=1}^{H} P_{t,h}^{G}\lambda_t^G\right) \le C_r = (1+\omega)C_0 \tag{23}$$

$$(1-\alpha)\tilde{\lambda}_t^G \le \lambda_t^G \le (1+\alpha)\tilde{\lambda}_t^G \tag{24}$$

$$(1-\alpha)\tilde{P}_{t,h}^{L} \le P_{t}^{L} \le (1+\alpha)\tilde{P}_{t,h}^{L} \quad (25)$$

(2) - (21) (26)

In the above formulation, α is the horizon of the uncertainty. The main goal of this formulation is maximizing the optimum value of the uncertain horizon while guaranteeing that the microgrid cost in the robustness mode, i.e., C^* will not exceed the critical cost of the microgrid (C_r). It should be noted that C_r is equal to $C_r = (1+\omega)C_0$ and C_0 is the deterministic value of the optimum cost of the microgrid. In this mathematical formulation, ω is the cost variation factor that is employed to set the risk averseness of the microgrid operator. It is an input parameter between 0 and 1. As the decision-maker becomes more risk-averse against the uncertain parameter, higher values for the cost deviation factor should be chosen. Constraints (24) and (25) indicate that the fractional uncertainty model for IGDT approach is used (Jasinski et al., 2023). In the above formulation, the maximum value for the microgrid cost will occur if the highest electrical load $P_{t,h}^{L}$ and electricity price λ_t^G would be selected as the uncertain parameters. Therefore, constraints (29) and (30) can be easily replaced by $\lambda_t^G = \tilde{\lambda}_t^G(1+\alpha)$ and $P_{t,h}^{L} = \tilde{P}_{t,h}^{L}(1+\alpha)$. Hence, the problem formulation can be simplified as follows:

$$\hat{\alpha}(q, C_r) = Maximize\ \alpha \quad (27)$$

s.t:

$$C^* \le C_r = (1+\omega)C_0 \quad (28)$$

$$\lambda_t^G = \tilde{\lambda}_t^G(1+\alpha) \quad (29)$$

$$P_{t,h}^{L} = \tilde{P}_{t,h}^{L}(1+\alpha) \quad (30)$$

(2) - (21) (31)

The solution of this optimization problem will provide the optimum horizon of the demand uncertainty for risk-averse decision-maker under different levels of the deviation factor, i.e. ω.

340 *3.2. Opportunity function of IGDT based method:*

341 Behavior of the risk-seeker decision-maker is being analyzed through an opportunity function
342 based on the IGDT approach. This function is formulated as:

$$\hat{\beta}(q, C_P) = minimize\ \alpha \tag{32}$$

343 *s.t:*

$$C^{\angle} = \ min\left(\sum_{t=1}^{T}\sum_{h=1}^{H} P_{t,h}^{G}\lambda_t^G\right) \le C_p = (1-\omega)C_0 \tag{33}$$

$$(1-\alpha)\tilde{\lambda}_t^G \le \lambda_t^G \le \ (1+\alpha)\tilde{\lambda}_t^G \tag{34}$$

$$(1-\alpha)\tilde{P}_{t,h}^{L} \le P_t^L \le \ (1+\alpha)\tilde{P}_{t,h}^{L} \tag{35}$$

(2) - (21) (36)

344 In the opportunity strategy of the IGDT approach, the main objective of this model is
345 minimizing the optimum value of the uncertain horizon while guaranteeing that the microgrid cost
346 in the opportunity mode, i.e., $C^{\angle}$ might be lower than the target cost of the microgrid (C_p), where
347 C_p is equal to $C_p = (1-\omega)C_0$ and C_0 is the deterministic value of the optimum cost of the
348 microgrid. In other words, the opportunity function is used to determine the possible reduction of
349 microgrid cost due to low load consumption. Thus, the low values for α is preferred. In the above
350 formulation, the minimum value for the microgrid cost will occur if the lowest electrical load $P_{t,h}^{L}$
351 and electricity price λ_t^G would be consumed as the uncertain parameters. Therefore, constraints
352 (34) and (35) can be easily replaced by $\lambda_t^G = \tilde{\lambda}_t^G(1+\alpha)$ and $P_{t,h}^{L} = \tilde{P}_{t,h}^{L}(1-\alpha)$. Hence, the
353 problem formulation can be simplified as follows:

$$\hat{\beta}(q, C_P) = minimize\ \alpha \tag{37}$$

354 *s.t:*

$$C^{\angle} \leq C_p = (1-\omega)C_0 \tag{38}$$

$$\lambda_t^G = \tilde{\lambda}_t^G(1+\alpha) \tag{39}$$

$$P_{t,h}^L = \tilde{P}_{t,h}^L(1-\alpha) \tag{40}$$

(2)-(21) (41)

The solution of this optimization problem will provide the optimum horizon of the demand uncertainty for risk seeker decision-maker under different levels of the deviation factor, i.e. ω.

4. Simulations

In this section, risk-based performance of local operator against the uncertainty of demand and electricity price is studied in a test system shown in Fig. 3. As it can be seen, there are two residential complexes, the complexes are connected to the upstream grid which is illustrated as a conventional power plant. Moreover, the PV panels are connected to each complex which covers a percentage of the demand of the microgrid. Finally, two EV parking lots are considered in this case that enable the complexes to charge or discharge their EVs. It should be noted that both complexes have PV solar systems and EV parking lots, demonstrating a shared commitment to renewable energy integration and sustainable transportation. On the other side, there are differences in a number of factors such as the energy consumption of each complex, the quantity of power generated by PV panels, the pattern of charging and discharging EVs in the parking lots.

The proposed model in the deterministic stage has a MILP formulation. Thus, the optimization problems of this stage can be solved by a MILP solver, such as CPLEX used in this paper. However, it is important to note that the IGDT-based model includes the multiplication of two variables, which introduces non-linearity into the problem. This nonlinearity in the optimization model arises from the multiplication of the decision variables, which are the horizon of the uncertainty to the load and also to the electricity price. Thus, the IGDT-based problem

formulations are formulated as mixed-integer non-linear programming (MINLP). The simulations are done using a general algebraic modeling system (GAMS). The DICOPT solver is employed to find the optimum solution and results are illustrated for different levels of uncertainty.

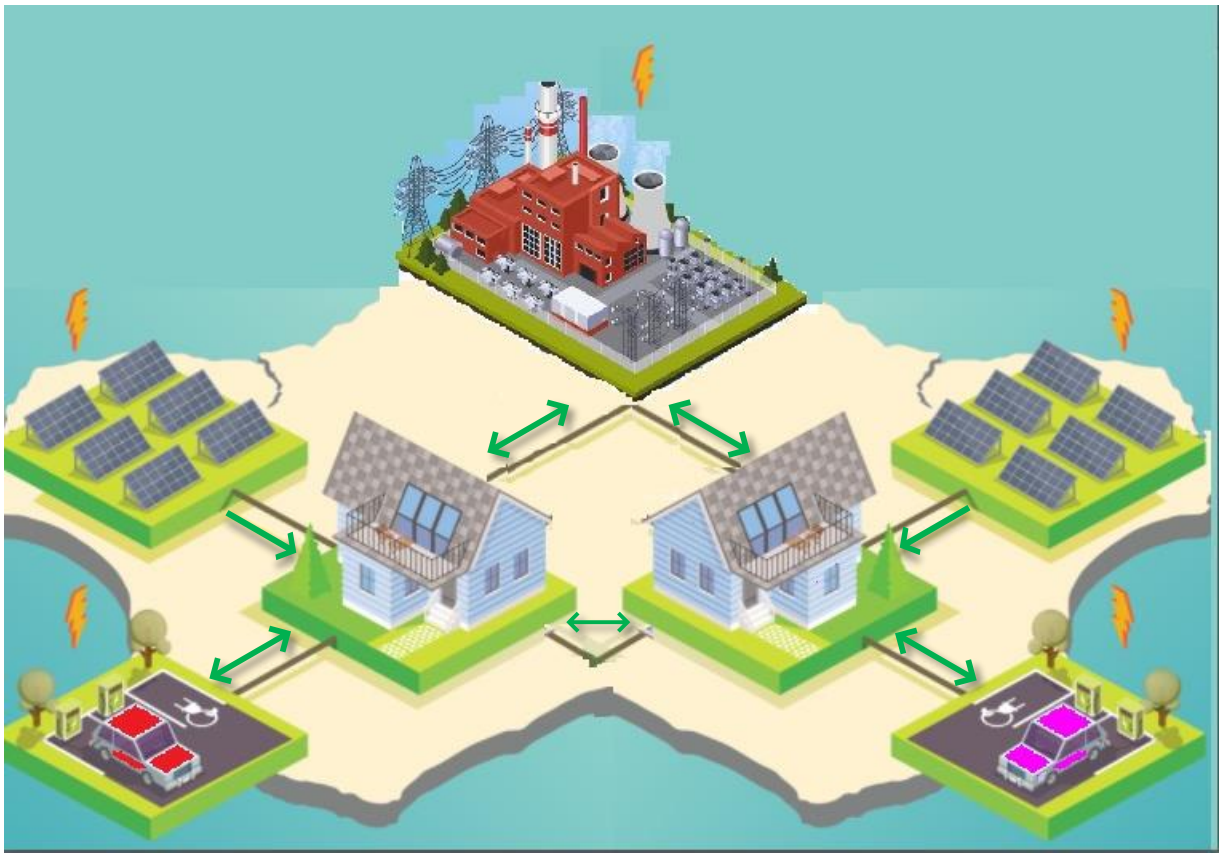


Fig. 3. The structure of the studied test system

4.1. Input data

Hourly expected electricity prices and expected load profiles are taken from (Zepter et al., 2019). The expected prices are presented in Fig. 4. Then, the reduced generated scenarios regarding the hourly output power of the PV panels are presented in Table 1. Based on the nominal installed capacity of the panels for each complex, the final value is different. The nominal installed capacities of the PV unit of Complex 1 and Complex 2 are 40 kW and 35 kW, respectively. Therefore, the amount of power generated by PV unit in Complex 1 would be higher than that in Complex 2. Furthermore, the arrival and departure patterns of EVs in each EV parking lot are

illustrated in Fig. 5. According to this figure, the arrival times of EVs to the EVPLs 1 and 2 are 12:00 and 9:00. While their departure times from the parking lots are 8:00 and 17:00.

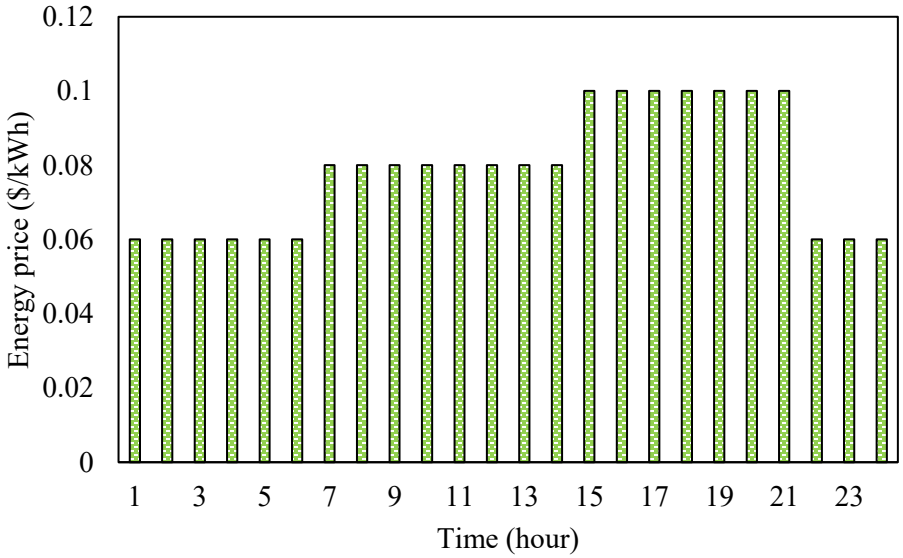


Fig. 4. The expected energy price s over the studies period

Table 2: The generation scenarios of PV panels

S / T	9	2	3	4	5	6	7	8	1	10	11	12	13	14	15
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0.095	0.089	0.082	0.094	0.089	0.09	0.093	0.084	0.085	0.1	0.089	0.103	0.081	0.093	0.069
6	0.511	0.316	0.412	0.404	0.424	0.41	0.403	0.464	0.417	0.522	0.418	0.45	0.438	0.455	0.424
7	0.684	0.89	0.82	0.729	1.058	0.889	1.065	0.969	0.77	0.947	0.954	0.938	0.917	0.834	0.972
8	1.241	1.059	1.23	1.212	1.068	1.043	1.125	1.242	1.014	1.121	1.048	1.21	1.079	1.238	0.894
9	1.49	1.888	1.622	1.71	1.627	1.703	1.742	1.807	1.8	1.809	1.679	1.66	1.661	1.604	2.091
10	1.904	1.974	1.919	1.641	1.745	1.65	1.26	1.723	2.084	1.867	1.829	1.782	1.708	1.81	1.938
11	1.535	1.747	1.829	1.778	1.516	1.716	1.647	1.487	1.837	1.569	1.791	1.685	1.801	1.602	1.314
12	2.069	1.636	2.018	1.967	1.691	1.397	1.815	1.909	1.752	1.463	1.716	1.774	1.823	1.839	1.805
13	1.374	1.129	1.191	1.027	0.983	1.406	1.1	1.195	1.237	1.062	1.065	1.119	1.341	1.134	1.096
14	0.752	0.719	0.714	0.655	0.726	0.64	0.76	0.569	0.662	0.797	0.685	0.728	0.751	0.624	0.737
15	0.685	0.681	0.811	0.878	0.813	0.739	0.695	0.787	0.765	0.865	0.761	0.757	0.668	0.639	0.689
16	0.876	0.81	0.752	0.757	0.661	0.728	0.777	0.697	0.791	0.618	0.681	0.716	0.604	0.757	0.724

17	0.606	0.756	0.765	0.746	0.658	0.682	0.737	0.606	0.695	0.648	0.695	0.823	0.729	0.657	0.652
18	0.302	0.405	0.37	0.334	0.309	0.392	0.365	0.415	0.302	0.365	0.337	0.391	0.326	0.352	0.347
19	0.064	0.075	0.066	0.068	0.063	0.075	0.073	0.065	0.064	0.071	0.081	0.072	0.058	0.06	0.078
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22		0	0	0	0	0	0	0	0	0	0	0	0	0	0
23		0	0	0	0	0	0	0	0	0	0	0	0	0	0
24		0	0	0	0	0	0	0	0	0	0	0	0	0	0

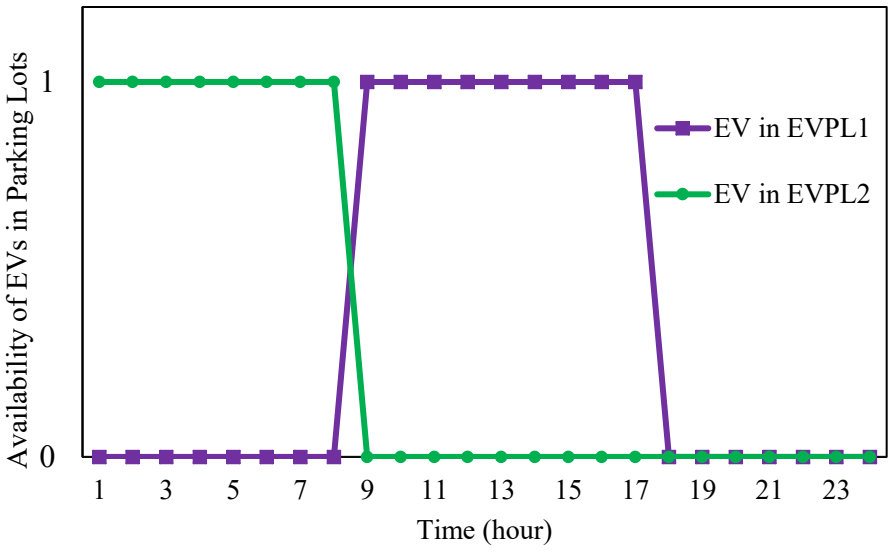


Fig. 5. The departure and arrival patterns of EVs in EVPL

The technical data of EV parking lots is presented in Table 3 (Jannati & Nazarpour, 2017) and (Seyyedeh Barhagh et al., 2020). This table provides crucial information regarding the specifications and characteristics of the EVPLs utilized in the studied system. It includes essential parameters such as maximum and minimum state of the charging, i.e., SOC_h^{Max} and SOC_h^{min} which represent the upper and lower limits of the battery's charge level, indicating the range within which the EVPL can operate effectively. Moreover, the EVPL's charging and discharging efficiency (η^{G2V} and η^{V2G}) shows the effectiveness of the EVPL which indicate the conversion rate of the electrical energy to charge the battery during the charging process and convert stored energy into electricity

power during the discharging process. The other parameters shown in Table 2 are the EVPL's maximum charge and discharge limits (P_{Max}^{Ch} and P_{Max}^{Dch}) and the maximum SOC difference limitation between two consecutive hours; that is ΔSOC^{EV}. This limitation specifies the acceptable range of SOC variation between consecutive time intervals, ensuring the stability and balance of the EVPLs' energy levels over time.

Table 3: EVPL characteristics

Parameter	$SOC_h^{\max}$	$SOC_h^{\min}$	$\Delta_{soc}^{\max}$	P_{Max}^{Ch}	P_{Max}^{Dch}	η^{G2V}	η^{V2G}
[Unit]	kWh	kWh	kWh	kW	kW	%	%
Value	4.5	0	1	1.5	1.5	95	90

4.2. Results and discussion

In this stage, the simulation results and discussion are presented. In the first step, it is assumed that there is no uncertainty and the microgrid operator has perfect information about the expected electricity price and load consumption values. This stage is called deterministic stage, i.e., Eqs. (1) – (22). In other words, it is considered that the forecasted values for these parameters are the same as the observed ones. In this situation, the proposed model is carried out on the studied case and the objective function is minimizing the microgrid cost considering the load and electricity price forecasts which is equal to $2938. It should be noted that further results about this step are presented and discussed in the following paragraphs as the risk-neutral strategy. As in the deterministic mode, the decision-maker is neutral against the risks associated by the uncertain parameter.

Then, in the next step, the uncertainty is taken into account. Therefore, the uncertainty posed through the load and electricity price is addressed through implementation of IGDT framework. To this end, IGDT robustness and IGDT opportunity approaches are applied for the risk-averse

and risk-seeking strategies, respectively. The main objective of risk-averse strategy is maximizing the horizon of the uncertainty (α) while guaranteeing that the final cost (C^*) will not be greater than the critical cost, i.e. C_r, presented in Eqs. (27) – (31). The risk level in the IGDT approach is the deviation cost denoted by ω which is chosen 0 to 0.5. In order to explain in detail, an arbitrary value for ω is chosen, i.e., 0.2. In this case, the critical microgrid cost will be $C_r = (1+\omega)C_0 = (1+0.2)\,\$2938 = \$3525$. In this case, after solving the optimization problem, the optimum IGDT robustness value $\hat{\alpha}(q, C_r)$ will be equal to 0.06. This means if the hourly uncertain parameters in load and price be 6% higher than the expected values (which is worser than the expected values), the decision-maker is certain that the final microgrid cost will not be higher than $\$3525$. Therefore, implementing a risk-averse strategy, manages the power supply sources in a way to respond to the increase in the load and electricity prices, which in turn leads to increase the operating cost of complexes 1 and 2, indicating the effectiveness of IGDT method in providing a suitable operation strategy for both complexes.

Management of the uncertainty through implementation of IGDT robustness approach imposes cost to the decision-maker. This cost is defined as the robustness cost. The robustness cost for different values of $\hat{\alpha}$ is depicted in Fig. 6. It is obvious from this figure that as the decision-maker desires to be more secure against the higher levels of uncertainty, the robustness cost increases as well. For instance, when $\hat{\alpha} = 0.06$, the robustness cost is equal to \$86.

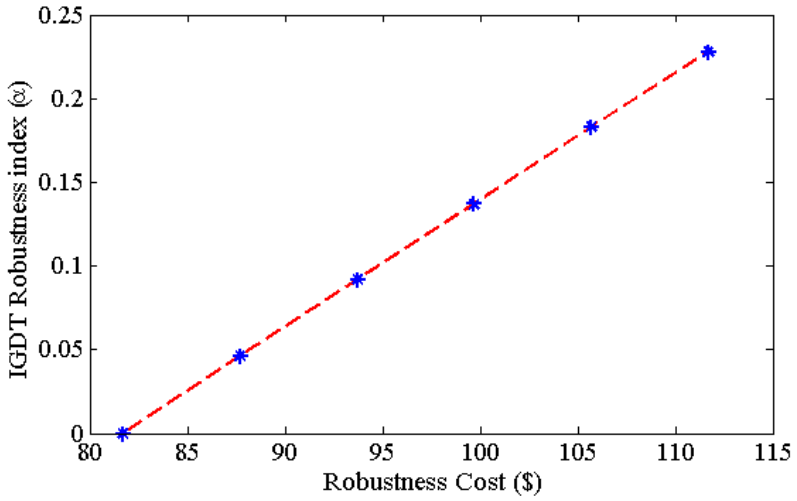


Fig. 6. The robustness cost for different robustness indexes

The impact of IGDT robustness approach on the risk-averse decision-making procedure is investigated in the previous paragraphs. Now, the risk-seeking strategy is investigated on the considered test system, presented in Eqs. (37) – (41). The main objective of this method is finding the minimum value of the uncertain horizon $\hat{\beta}(q, C_P)$ which if the load and prices deviate favorably in that amount, the decision-maker might reach to lower final microgrid cost ($C^{\angle}$) than the target cost (C_p). Similar to the risk-averse strategy, different risk- levels are chosen, $\omega \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5\}$. The same arbitrary value for the cost deviation factor is also chosen. In this case, the target cost will be $C_p = (1-\omega)C_0 = (1-0.2)\$2938 = \$2350$. In this case, after solving the optimization problem, the optimum IGDT opportunity value $\hat{\beta}(q, C_r)$ will be equal to 0.075. Therefore, if the load and the electricity prices would be at least 7.5% lower than the forecasted values (favorable scenario), the final microgrid cost might be $\$2350$.

Similar to robustness cost, application of IGDT opportunity function imposes cost to the final microgrid cost; called opportunity cost. The opportunity cost for different values of $\hat{\beta}$ is depicted in Fig. 8. It can be seen that higher tendency for lower target costs will lead to an increase in the opportunity cost. For example, when $\hat{\beta} = 0.075$, the opportunity cost is equal to \$69. On the other

hand, as shown in Fig. 7, reducing in the electrical load demand and experiencing lower electricity prices decrease the operation cost of complexes. This reduction in the uncertain parameters can provide the system operator to take this opportunity and thus managing the energy resources in an optimal way to reduce the cost.

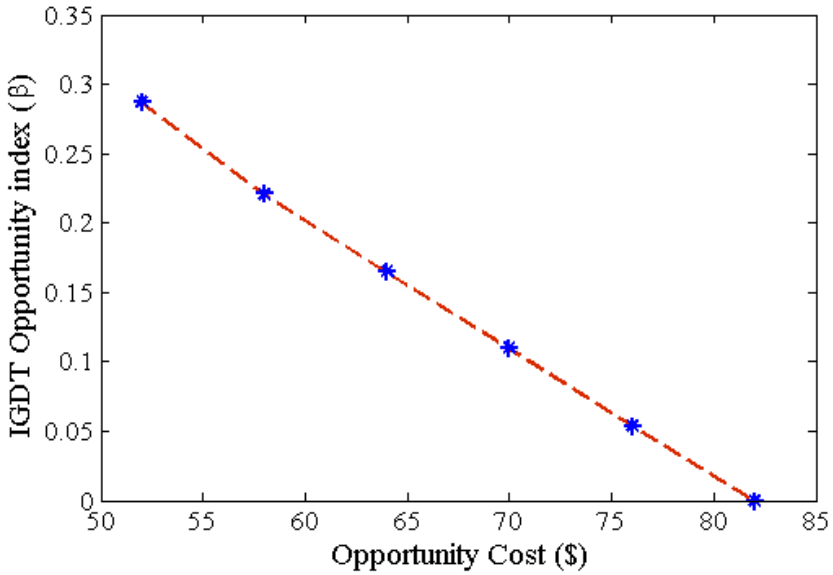


Fig. 7. The opportunity cost for different opportunity indexes

The amount of the purchased power from the upstream grid to meet the electrical load demand of complexes 1 and 2 is depicted in Fig. 8 for three different types of decision-makers such as risk-averse (RA) risk-neutral (RN) and risk-taker (RT). Implementation of the proposed model for different decision makers can provide a clear view of the system's performance under different risk levels. As illustrated, the operator can reduce the purchased power during expensive hours (e.g., 7:00-16:00) by managing the local power generation sources such as PV unit and EVPL. In the early hours of the studied period, the purchased power from upstream network in all risk strategies increase to provide the demand of the complexes 1 and 2, as well as some amount of energy of the EVPL required to charge EVs. The purchased power during these hours increases in the RA mode in order to compensate the load growth under uncertainty. On the other hand, in the

semi-peak period (7:00-16:00), the purchased power decreases in all three studied cases. In more detail, due to the higher price of power during these hours and the load reduction, the purchased power from the upstream network is close to zero. This shows the efficiency of the proposed model in using the best strategy for management of the local resources, reduction in the operation cost, and handling the uncertainties in complexes 1 and 2. According to Fig. 8, in the last hours of the studied period, the purchased power is proportional to the peak of load demand in complexes 1 and 2. Similarly, in these hours, the operator uses the strategies provided by IGDT method to provide the required demand under uncertainty in complexes 1 and 2, which reduces the operating costs in both complexes. Since the strategies designed by IGDT approach allow management of electrical load in complexes 1 and 2, which leads to the ease of managing the power resources in the supply side of each residential complex. The total purchased power from the upstream network to supply the load of each of complexes 1 and 2 in different levels of load uncertainty is shown in Fig. 9.

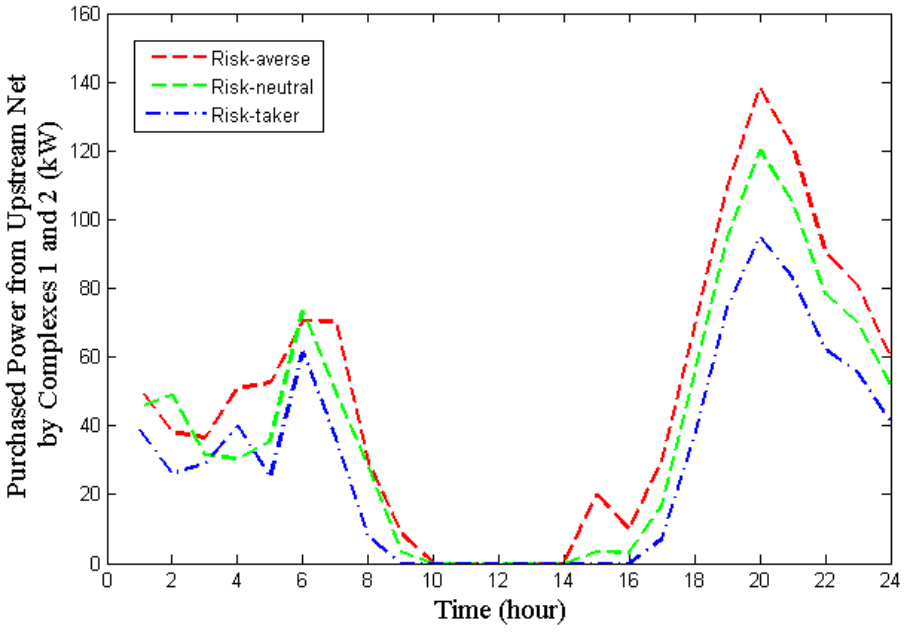


Fig. 8. The purchased power from the upstream grid in complexes for various risk strategies.

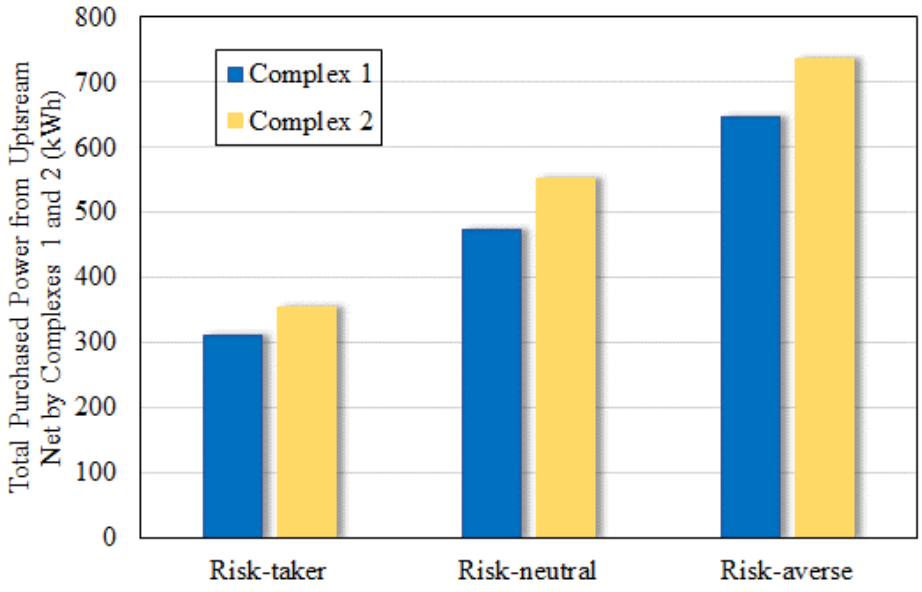
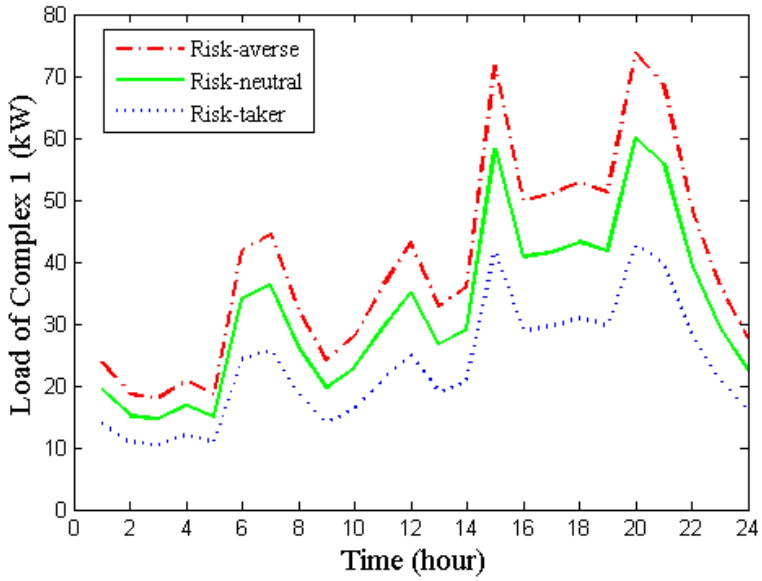


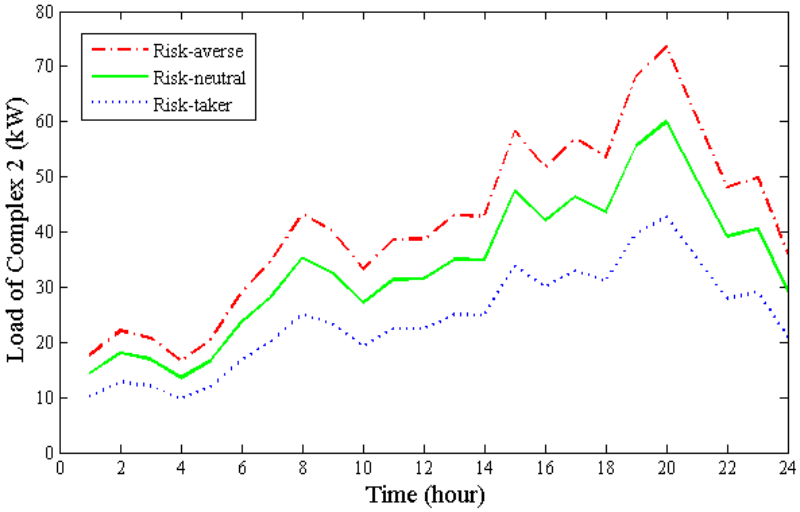
Fig. 9. The total purchased power from the upstream grid in complexes 1 and 2 for various risk strategies.

Regarding Figures 10 and 11 which are stating the load profile of the complex 1 and complex 2, the consumption of each end-user is dependent to several factors such as the EV charging and discharging period, type of the EV, number of the people living in each complex and the electrical equipment being used. All of these factors result in having a different load profile for the studied case. As shown in these figures, the uncertainty can be considered an unpredictable condition. Due to the uncertainty, the load demand increases in complexes 1 and 2, as shown in red color in Figs. 10 and 11. To manage the supply sources and meet energy demand, which is increased due to the uncertainty, the operator can implement a risk-averse strategy. On the other hand, the load demand can decrease due to the uncertainty, as shown in blue. In this case operator can implement risk-taker strategy to manage resources and thus reduce the operation cost of complexes. It is noteworthy that the load demand in normal condition is illustrated in green color in Figs. 10 and 11.



505

506 Fig. 10. The load profile of complex 1 in the studied period in three risk strategies



507

508 Fig. 11. The load profile of complex 2 in the studied period in three risk strategies

509 The amount of power of EVs in charging and discharging conditions in the EVPL of complexes
510 1 and 2 are presented in Figs. 12 and 13. In Fig. 12, according to the parking hours of EVs in
511 complex 1, the operator charges EVs in the early hours of the studied period, in which the energy
512 price is low. While in the other hours of the period when the energy price is high, the operator
513 takes advantage of available energy in the EVPL to discharge EVs and balance the electric demand
514 in three different risk strategies (i.e., RA, RN and RT).

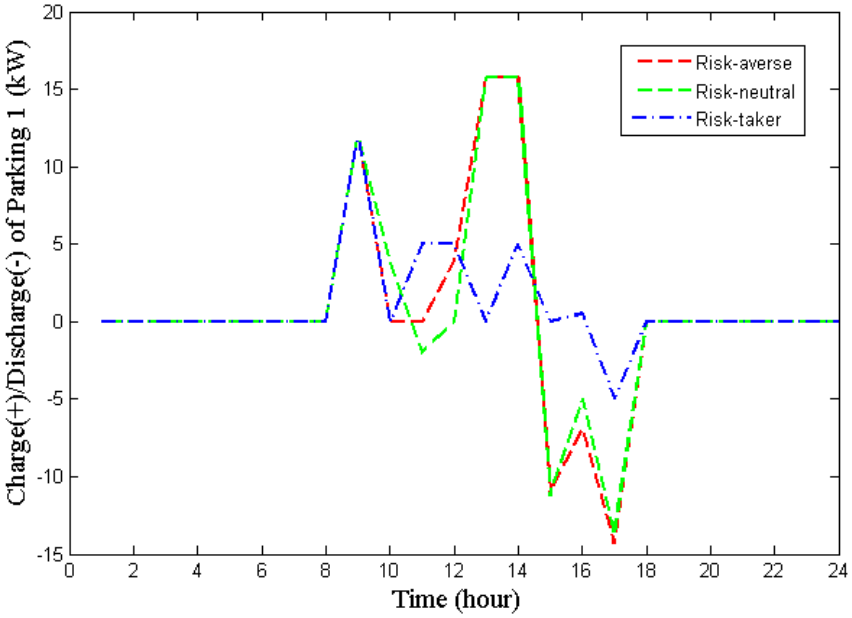


Fig. 12. The SOC of EVPL in complex 1 in three risk strategies

In Fig. 13, considering the available charging capacity of EVs in the parking lot, the operator deploys the PV unit to charge the EVs. Once charged, the stored energy is discharged to supply load demand in peak time periods. This shows the efficiency of the proposed model to manage the energy supply sources (i.e., PVs and EVs) and increase the energy efficiency in the operation of studied complexes, which not only avoids loss of energy but also supplies a portion of peak load demand to reduce the operation cost in peak time periods.

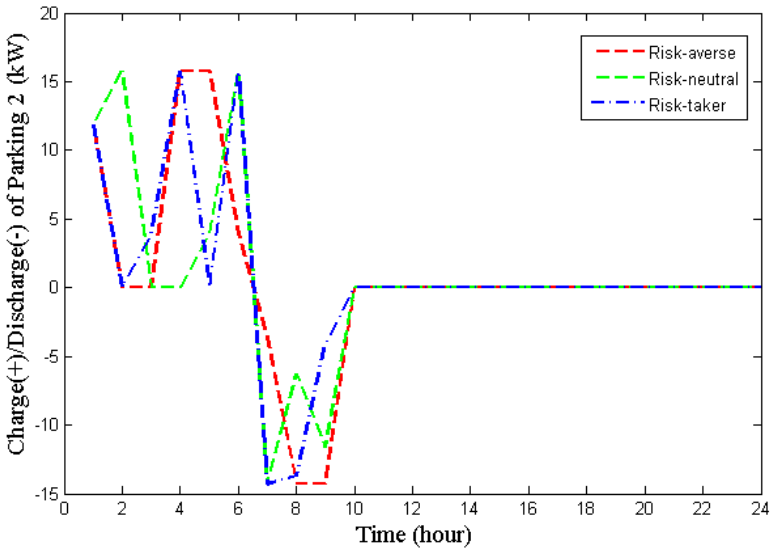


Fig. 13. The SOC of EVPL in complex 2 in three risk modes

Fig. 14 shows the exported power complex 2 to complex 1. In the RA strategy, due to the uncertainty that increases the electric load and price, as well as the limitation of distributed generation resources in complex 2, the exported power to complex 1 decrease. However, in the RT strategy, due to possible reduction in the uncertain parameters, i.e., electric load and price of complex 2, the operator decides to increase the power transfer from complex 2 and supply load demand in complex 1. Moreover, considering the fact that EVs are not available in the EVPL of complex 2 during the day, excess generation by PV unit in this complex is supplied to complex 1 to either serve the load or charge the EVs.

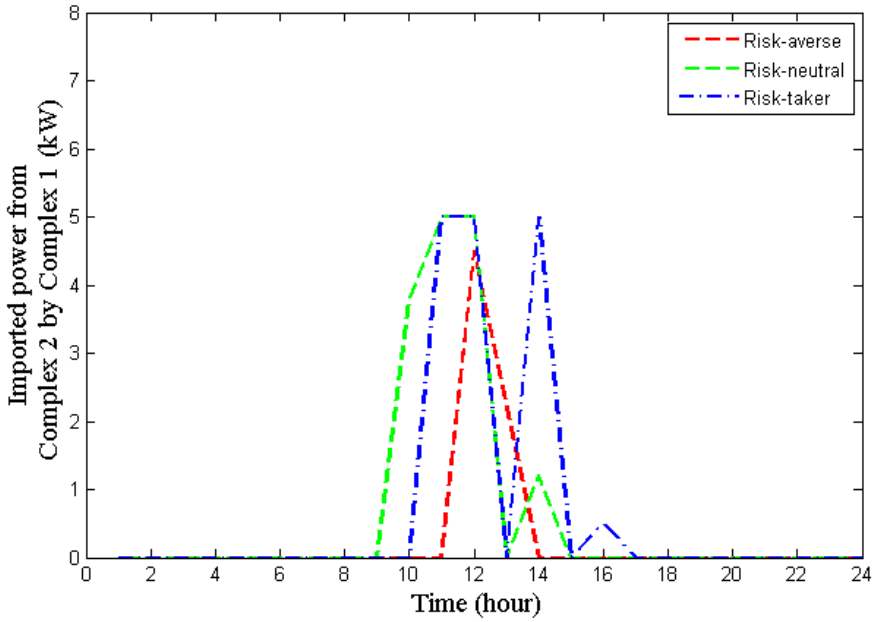


Fig. 14. The imported power profile from complex 2 to complex 1.

Our study demonstrated the effectiveness of application of different decision-making strategies through implementation of the IGDT framework in managing the uncertain parameters. Two uncertainties are considered in this study, i.e., the electricity prices and the load consumption. The risk-averse strategy resulted in an increased power purchase from the upstream grid. This decision was motivated by the desire to mitigate potential negative impacts on the uncertain parameters. Therefore, the least amount of the P2P transaction accrued when the risk-averse strategy is chosen happened only in one of the studied hours of the whole period. While the number of hours and values the risk-taker decision-maker made energy transactions through P2P method with the other complex is 4 times higher. This can prove the strategy of a risk-taker microgrid operator that seeks to have lower microgrid costs in case of having a favorable deviation in the observed uncertain parameters compared to their forecasted values.

One of the other most important key findings of the result is related to the costs posed to the total cost through implementation of the risk-measure, i.e., IGDT. It can be seen that the robustness

549 and opportunity costs are essential to be measured before taking the decision. This cost has a direct
550 relation with the level of risk averseness or willingness. For the lower risk levels, low robustness
551 or opportunity costs are gotten. However, if the operator desires to be secure against the higher
552 deviations of the uncertain parameters, higher costs will be imposed to the total microgrid cost.
553 For instance, if the uncertain parameters deviate 10 unfavorably from the expected values, $93
554 will be the robustness cost.

555 **5. Conclusion**

556 In this paper, an optimal uncertainty-based operation of a local operator with two energy
557 complexes under the concept of local P2P trading is proposed. The primary objective was to assess
558 the performance of the local operator considering different levels of uncertainty such as risk-
559 neutral, risk-averse, and risk-seeking strategies. To achieve this, IGDT framework was employed
560 to study the effects of uncertainty such as the electrical load and electric price. The findings
561 presented in this work demonstrated that the application of IGDT and the consideration of different
562 decision-making strategies were essential in achieving optimal operation in the face of uncertainty.
563 Thus, the robust function of IGDT was utilized to address uncertainty in the risk-averse mode,
564 where the decision-maker aimed to protect the system against potential negative impacts. In
565 contrast, the opportunity function of IGDT was employed to address uncertainty in the risk-seeking
566 mode, allowing the decision-maker to exploit potential benefits arising from uncertainty.

567 The results revealed distinct behaviors of decision-makers under different strategies. The risk-
568 averse decision-maker showed a willingness to increase purchased power from the upstream grid,
569 maximizing the horizon of uncertainty. This approach aimed to ensure system resilience and
570 minimize potential risks in case of unfavorable deviations on the load and price. On the other hand,
571 the risk-seeking decision-maker adopted an opportunity function of IGDT method by decreasing
572 the purchased power from the upstream grid, aiming for significant cost reductions and targeting

on favorable uncertain conditions. Furthermore, we also investigated the operation of other units, such as renewables energy resources and EV parking lots, within the context of optimal P2P local trading in a microgrid. This analysis demonstrated that by employing reasonable strategies, enabled by optimal P2P trading, the overall system performance could be optimized not only in normal operation scenarios but also under uncertainties. For the future directions of the work, the decentralized approach can be investigated in order to examine the dynamics of resource allocation, price negotiation, and the potential benefits of incorporating P2P energy trading in microgrid systems.

References

Almenning, O. M., Bjarghov, S., & Farahmand, H. (2019). Reducing Neighborhood Peak Loads with implicit Peer-to-Peer energy trading under Subscribed Capacity tariffs. *SEST 2019 - 2nd International Conference on Smart Energy Systems and Technologies*. https://doi.org/10.1109/SEST.2019.8849067

Belgioioso, G., Ananduta, W., Grammatico, S., & Ocampo-Martinez, C. (2022). Operationally-Safe Peer-to-Peer Energy Trading in Distribution Grids: A Game-Theoretic Market-Clearing Mechanism. *IEEE Transactions on Smart Grid*. https://doi.org/10.1109/TSG.2022.3158442

Bjarghov, S., Naversen, C. Ø., Thorvaldsen, K., & Farahmand, H. (2019). *A Three-Stage Stochastic Peer-to-Peer Market Clearing Model with Real-Time Reserve Activation*.

Chen, K., Lin, J., & Song, Y. (2019). Trading strategy optimization for a prosumer in continuous double auction-based peer-to-peer market: A prediction-integration model. *Applied Energy*, *242*, 1121–1133. https://doi.org/10.1016/j.apenergy.2019.03.094

Cui, S., Wang, Y. W., & Xiao, J. W. (2019). Peer-to-peer energy sharing among smart energy buildings by distributed transaction. *IEEE Transactions on Smart Grid*. https://doi.org/10.1109/TSG.2019.2906059

Espadinha, J., Baptista, P., & Neves, D. (2023). Assessing P2P energy markets contribution for 2050 decarbonization goals. *Sustainable Cities and Society*, *92*, 104495. https://doi.org/10.1016/J.SCS.2023.104495

Fernandez, E., Hossain, M. J., Mahmud, K., Nizami, M. S. H., & Kashif, M. (2021). A Bi-level optimization-based community energy management system for optimal energy sharing and trading among peers. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2020.123254

Hahnel, U. J. J., Herberz, M., Pena-Bello, A., Parra, D., & Brosch, T. (2020). Becoming prosumer: Revealing trading preferences and decision-making strategies in peer-to-peer energy communities. *Energy Policy*. https://doi.org/10.1016/j.enpol.2019.111098

Haider, S., Rizvi, R. e. Z., Walewski, J., & Schegner, P. (2022). Investigating peer-to-peer power transactions for reducing EV induced network congestion. *Energy*, *254*, 124317. https://doi.org/10.1016/J.ENERGY.2022.124317

Hutty, T. D., Pena-Bello, A., Dong, S., Parra, D., Rothman, R., & Brown, S. (2021). Peer-to-peer electricity trading as an enabler of increased PV and EV ownership. *Energy Conversion and Management*. https://doi.org/10.1016/j.enconman.2021.114634

Jannati, J., & Nazarpour, D. (2017). Optimal energy management of the smart parking lot under demand response program in the presence of the electrolyser and fuel cell as hydrogen storage system. *Energy Conversion and Management*. https://doi.org/10.1016/j.enconman.2017.02.030

Jasinski, M., Najafi, A., Homaee, O., Kermani, M., Tsaousoglou, G., Leonowicz, Z., & Novak, T. (2023). Operation and Planning of Energy Hubs Under Uncertainty - A Review of Mathematical Optimization Approaches. *IEEE Access*, *11*, 7208–7228. https://doi.org/10.1109/ACCESS.2023.3237649

Liu, X., Chen, X., Jin, T., Liu, Z., Liu, Y., Su, M., Li, C., & Wu, Q. (2023). Network-Constrained Peer-to-Peer energy trading for multiple microgrids considering zoning pricing. *International Journal of Electrical Power & Energy Systems*, *147*, 108837. https://doi.org/10.1016/J.IJEPES.2022.108837

Long, C., Wu, J., Zhou, Y., & Jenkins, N. (2018). Peer-to-peer energy sharing through a two-stage aggregated battery control in a community Microgrid. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2018.05.097

Melendez, K. A., Subramanian, V., Das, T. K., & Kwon, C. (2019). Empowering end-use consumers of electricity to aggregate for demand-side participation. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2019.04.092

Nguyen, S., Peng, W., Sokolowski, P., Alahakoon, D., & Yu, X. (2018). Optimizing rooftop photovoltaic distributed generation with battery storage for peer-to-peer energy trading. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2018.07.042

Seyyedeh Barhagh, S., Abapour, M., & Mohammadi-Ivatloo, B. (2020). Optimal scheduling of electric vehicles and photovoltaic systems in residential complexes under real-time pricing mechanism. *Journal of Cleaner Production*, *246*, 119041. https://doi.org/10.1016/j.jclepro.2019.119041

Siano, P., De Marco, G., Rolan, A., & Loia, V. (2019). A Survey and Evaluation of the Potentials of Distributed Ledger Technology for Peer-to-Peer Transactive Energy Exchanges in Local Energy Markets. *IEEE Systems Journal*. https://doi.org/10.1109/JSYST.2019.2903172

Sorin, E., Bobo, L., & Pinson, P. (2019). Consensus-Based Approach to Peer-to-Peer Electricity Markets with Product Differentiation. *IEEE Transactions on Power Systems*. https://doi.org/10.1109/TPWRS.2018.2872880

Soto, E. A., Bosman, L. B., Wollega, E., & Leon-Salas, W. D. (2021). Peer-to-peer energy trading: A review of the literature. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2020.116268

Suthar, S., Cherukuri, S. H. C., & Pindoriya, N. M. (2023). Peer-to-peer energy trading in smart grid: Frameworks, implementation methodologies, and demonstration projects. *Electric Power Systems Research*, *214*, 108907. https://doi.org/10.1016/J.EPSR.2022.108907

Talari, S., Khorasany, M., Razzaghi, R., Ketter, W., & Gazafroudi, A. S. (2022). Mechanism design for decentralized peer-to-peer energy trading considering heterogeneous preferences. *Sustainable Cities and Society*, *87*, 104182. https://doi.org/10.1016/J.SCS.2022.104182

Tushar, W., Saha, T. K., Yuen, C., Morstyn, T., McCulloch, M. D., Poor, H. V., & Wood, K. L. (2019). A motivational game-theoretic approach for peer-to-peer energy trading in the smart grid. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2019.03.111

Tushar, W., Saha, T. K., Yuen, C., Morstyn, T., Nahid-Al-Masood, Poor, H. V., & Bean, R. (2020). Grid Influenced Peer-to-Peer Energy Trading. *IEEE Transactions on Smart Grid*, *11*(2), 1407–1418. https://doi.org/10.1109/TSG.2019.2937981

650 Tushar, W., Yuen, C., Mohsenian-Rad, H., Saha, T., Poor, H. V., & Wood, K. L. (2018). Transforming energy
651 networks via peer-to-peer energy trading: The potential of game-theoretic approaches. *IEEE Signal*
652 *Processing Magazine*. https://doi.org/10.1109/MSP.2018.2818327
653 Tushar, W., Yuen, C., Saha, T. K., Morstyn, T., Chapman, A. C., Alam, M. J. E., Hanif, S., & Poor, H. V. (2021).
654 Peer-to-peer energy systems for connected communities: A review of recent advances and emerging
655 challenges. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2020.116131
656 Wörner, A., Meeuw, A., Ableitner, L., Wortmann, F., Schopfer, S., & Tiefenbeck, V. (2019). Trading solar
657 energy within the neighborhood: field implementation of a blockchain-based electricity market. *Energy*
658 *Informatics*. https://doi.org/10.1186/s42162-019-0092-0
659 Xia, Y., Xu, Q., Huang, Y., & Du, P. (2023). Peer-to-peer energy trading market considering renewable energy
660 uncertainty and participants' individual preferences. *International Journal of Electrical Power & Energy*
661 *Systems*, *148*, 108931. https://doi.org/10.1016/J.IJEPES.2022.108931
662 Yang, Y., Chen, Y., Hu, G., & J. Spanos, C. (2022). Optimal Network Charge for Peer-to-Peer Energy Trading:
663 A Grid Perspective. *IEEE Transactions on Power Systems*. https://doi.org/10.1109/TPWRS.2022.3185585
664 Zepter, J. M., Lüth, A., Crespo del Granado, P., & Egging, R. (2019). Prosumer integration in wholesale
665 electricity markets: Synergies of peer-to-peer trade and residential storage. *Energy and Buildings*, *184*, 163–
666 176. https://doi.org/10.1016/j.enbuild.2018.12.003
667 Zhang, Z., Li, R., & Li, F. (2020). A Novel Peer-to-Peer Local Electricity Market for Joint Trading of Energy
668 and Uncertainty. *IEEE Transactions on Smart Grid*, *11*(2), 1205–1215.
669 https://doi.org/10.1109/TSG.2019.2933574
670 Zhao, F., Li, Z., Wang, D., & Ma, T. (2023). Peer-to-peer energy sharing with demand-side management for fair
671 revenue distribution and stable grid interaction in the photovoltaic community. *Journal of Cleaner*
672 *Production*, *383*, 135271. https://doi.org/10.1016/J.JCLEPRO.2022.135271
673
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675