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A R T I C L E I N F O

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A B S T R A C T

The integration of hydrogen vehicles into citizen-oriented energy communities presents a transformative opportunity to enhance energy resilience, sustainability, and democratization. With zero-emission profiles and rapid refueling capabilities, hydrogen vehicles are pivotal in advancing cleaner transportation solutions. However, uncertainties in driving patterns and refueling behaviors pose challenges to their seamless integration and management. This paper proposes a framework based on information gap decision theory (IGDT) to address these uncertainties within community hydrogen parking lots. These parking lots also function as community energy storage systems, utilizing electrolyzers, fuel cells, and hydrogen storage to manage both hydrogen and electrical energy. The approach facilitates energy sharing among prosumers while ensuring thermal comfort within the community. Results show that under a risk-averse strategy, the system tolerates up to 50% variability in travel distances without exceeding cost limits, while a risk-seeking strategy accommodates up to 60% variability at a 50% deviation factor.

1. Introduction

1.1. Motivation

The emergence of citizen energy communities (CECs) has marked a pivotal shift in the energy landscape [1]. These communities not only enhance energy resilience and independence but also foster sustainable practices by integrating renewable energy sources [2]. By decentralizing energy production and involving citizens directly, they contribute significantly to reducing carbon footprints and promoting energy democratization, aligning with global sustainability goals [3]. In this context, the adoption of hydrogen vehicles (HVs) has surged due to their potential to offer zero-emission transportation solutions and their role in supporting the energy transition [4]. HVs offer performance comparable to conventional vehicles, with a 650 km range, 280-s refueling time for 4.34 kg of hydrogen, and fuel savings of 10.2–11.0 ¢/km. Using green hydrogen can reduce greenhouse gas emissions to 4.7 gCO_2/km, making HVs a competitive and eco-friendly alternative to fossil fuel vehicles [5]. To maximize the benefits of HVs, it is crucial to integrate them into CEC and manage their operation in a manner that supports the overall energy ecosystem [6]. To improve the management of HVs in energy systems, parking facilities equipped with hydrogen or electricity storage systems can play a pivotal role. Hydrogen, as an energy carrier, enables long-term storage of surplus energy generated from renewable sources, while batteries are particularly suitable for short-term storage [7]. The integration of these two technologies with vehicle parking systems helps optimize energy consumption and storage, leading to increased energy community flexibility, reduced operational costs within the community, and lower greenhouse gas emissions [8].

However, in the context of HV parking lots, where human behavior such as driving patterns plays a key role, the inherent complexity and unpredictability of these behaviors make accurate forecasting based solely on historical data highly challenging [9]. Human behavior is influenced by a wide range of dynamic factors, including environmental changes, personal preferences, social influences, and even momentary psychological conditions [10]. All of these contribute to instability and uncertainty in predictions based on historical data. While historical data may reveal general trends, they lack the ability to account for sudden changes or atypical behaviors [11]. To address these challenges, information gap decision theory (IGDT) provides a robust framework for

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decision-making under severe uncertainty. Unlike traditional probabilistic approaches, IGDT accommodates situations where precise probability distributions are unavailable or unreliable. It allows for modeling varying levels of risk attitudes, offering decision-makers the flexibility to adopt either risk-averse or risk-seeking strategies depending on their tolerance for uncertainty. This adaptability makes IGDT particularly well-suited for managing HV parking systems, where human behavior introduces significant unpredictability. By incorporating risk attitudes, IGDT enables the development of solutions that align with specific operational or strategic objectives.

Therefore, to address this uncertainty and enhance decision-making accuracy, a model is required that is robust against these behavioral fluctuations and unpredictability.

1.2. Literature review

CECs promote a decentralized and resilient energy system by empowering individuals and local groups to actively participate in the energy market [12]. [13] highlighted that CECs can optimize local energy use, reduce costs, and enhance energy independence. Furthermore, CECs play a crucial role in the energy transition by enabling local generation and storage, which contributes to the reduction of carbon emissions and promotes sustainable energy use [14]. Additionally, one of the notable features of CECs is the capability for energy sharing while [14], and [15,16], explored the performance and mechanisms of energy sharing within energy communities and demonstrated its impact. [17] introduces an energy-sharing framework for CECs, incorporating a purification subsystem to optimize hydrogen trading and reduce operating costs. [18] proposed an energy market framework that integrates hydrogen and electric vehicles into microgrids, achieving an 8.08% cost reduction through energy sharing. Furthermore, a key goal of CECs is to maintain the thermal comfort of prosumers that is addressed by several works in the literatures like [19–21].

Moreover, HVs in the CECs platform offer a zero-emission transportation solution with the potential for rapid refueling and long driving ranges [22]. The integration of HVs into energy systems can significantly contribute to reducing greenhouse gas emissions [23]. [24] investigated the operational strategies for fuel cell power supply systems to enhance the durability of commercial HVs. HVs can provide services such as peak shaving, load balancing, and backup power supply during grid outages [25]. [26] proposed a coordinated hydrogen supply infrastructure planning model that integrates transportation and energy networks. [27] proposed a model based on the operation of battery and fuel cell HVs and the expansion of charging and hydrogen refueling infrastructure to decarbonize road transport through microgrids. [28] presented an optimization methodology to improve the hydrogen lifecycle, emphasizing renewable energy, efficient storage, and integrating HVs to support decarbonization and sustainability goals. [29] focused on optimizing electric microgrid designs for HVs and refueling stations, leveraging renewable energy and advanced energy management strategies, respectively. [30] underscored the importance of energy management strategies (EMSs) in HV performance, addressing AI-based methods, as well as the evolution of EMSs, including rule-based and optimization-based approaches. [31] proposed an energy management framework for HVs with renewable energy systems and hydrogen storage, incorporating risk management and demand response programs.

Recent studies on HVs highlight the importance of optimizing energy management under uncertainty. As demonstrated in various works, both the availability of HVs in parking lots and the distances they travel introduce significant uncertainties that can impact the overall energy system [32]. These uncertainties stem from operational variations, component performance, and external factors like driving conditions. Studies such as those by [33,34] emphasized the critical role that dynamic control strategies play in mitigating these uncertainties by utilizing advanced methods like neural networks and predictive algorithms. Similarly, [35,36] explored integrated energy management systems that adjust to real-time conditions to ensure optimal performance, even in the face of fluctuating variables.

Community-based hydrogen storage systems are gaining significant attention as a practical solution compared to individual hydrogen storage systems. The high capital cost of hydrogen storage equipment, including advanced storage tanks, compressors, and safety systems, renders individual ownership financially impractical for most users. Several studies have explored the design and optimization of community-based hydrogen storage systems. [37] highlighted the economic benefits of a communal hydrogen storage system, demonstrating its efficiency and reliability for end-user applications. Similarly, [38] emphasized that large-scale hydrogen storage facilities optimize long-term energy storage, offering both environmental and economic benefits to renewable energy communities. These findings are supported by the work of [39], which details the operational advantages of hydrogen generation and storage in community systems, enabling higher flexibility and integration with renewable energy sources. [40] proposed a dynamic programming approach to optimize hybrid energy systems in microgrids, integrating photovoltaics, fuel cells, electrolyzers, hydrogen storage, and batteries. The method outperforms genetic algorithms, enhancing photovoltaic utilization by 0.95% and fuel economy by nearly 50%. All these studies have examined the role and importance of community-based hydrogen storage systems while some studies have also focused on hydrogen storage in hydrogen vehicle parking lots. As an example, [41] examined the role of hydrogen storage in electric vehicle parking lots and demonstrated that integrating hydrogen storage with such parking facilities can reduce operating costs by up to 42%. An optimal model for energy management of hydrogen storage systems in hydrogen vehicle parking lots proposed by [42]. [43] proposed an optimal energy management strategy for a combined heat, hydrogen, and power microgrid incorporating electric and hydrogen vehicle parking lots. Therefore, all previous studies have examined the role and effectiveness of hydrogen storage systems in the context of CECs or HV parking lots. However, no model has yet been proposed for the optimal and efficient utilization of hydrogen storage systems in HV parking lots that can serve as community-based hydrogen storage systems. To highlight the main research gaps in the literature, Table 1 presents a comparative taxonomy of key factors in hydrogen vehicle integration within energy communities. Based on the literature review and the taxonomy table, the primary research gaps identified in the literature are as follows:

- **Integrated energy management framework**: Existing studies often address individual aspects, such as energy sharing or hydrogen storage ([14,15,17]), but fail to provide a holistic framework that integrates energy sharing, hydrogen parking lots, community hydrogen storage, and thermal comfort for citizen energy communities.
- **Uncertainty in hydrogen vehicle behavior**: While some works ([26,27,34]) explore uncertainty in HV behavior, they primarily rely on scenario-based or predictive algorithms, lacking a robust and adaptable framework like IGDT to manage traveling distance uncertainties effectively.
- **Lack of integrated models for dual-purpose hydrogen storage systems in parking lots:** Existing studies ([37–43]) have primarily focused on hydrogen storage systems in parking lots, treating them as separate operational assets for parking facilities and as communal energy storage solutions for the broader community. However, incorporating HV driving patterns alongside the dual-purpose functionality of these hydrogen storage systems remains a significant research gap in the literature.

1.3. Contribution

This paper introduces a novel framework that employs IGDT to manage the travel uncertainty of HVs within CEC hydrogen parking lots.

Table 1
Comparison of the proposed model with closely related studies.

Refs.	Energy sharing	Hydrogen parking lot	Hydrogen community storage	Thermal comfort	Traveling distance uncertainty of HVs	Optimization type
[5]	×	×	✓	×	Predictive algorithm	NLP
[14]	✓	×	×	×	×	MILP
[15]	✓	×	×	✓	×	MILP
[16]	✓	✓	✓	×	×	MINLP
[17]	✓	×	✓	×	×	MILP
[18]	✓	✓	✓	×	×	MIQCP
[21]	×	×	×	✓	×	MILP
[22]	×	✓	✓	×	×	MILP
[23]	×	✓	×	×	×	MINLP
[25]	×	×	✓	×	×	MILP
[26]	×	✓	×	×	Scenario-based	MINLP
[27]	×	✓	✓	×	Scenario-based	MILP
[30]	×	✓	×	×	Data-driven	×
[31]	×	✓	✓	×	Robust	MILP
[34]	×	✓	✓	×	Predictive algorithm	MILP
[42]	×	✓	✓	✓	×	MILP
This paper	✓	✓	✓	✓	IGDT	MILP

A significant contribution of this research is the development of a comprehensive CEC model that integrates various hydrogen energy components, including HVs, hydrogen storage tanks, electrolyzers, and fuel cells. This model provides a holistic approach to energy management by embedding hydrogen technologies into the community energy ecosystem, thereby enhancing both operational flexibility and sustainability. It accounts for the synergistic roles of these components, supporting the direct use of HVs as zero-emission transportation and enabling efficient hydrogen production, storage, and utilization within the community. Additionally, the paper presents an IGDT-based framework designed to manage the unpredictability of driving patterns and refueling behaviors of HVs, ensuring robust decision-making under conditions of severe uncertainty. This approach contributes to the reliable and optimal operation of energy systems within CECs, significantly improving their overall resilience and adaptability. The primary contributions of this work can be analyzed and summarized as follows.

- **Development of an optimal prosumer-centric energy management model for CECs, incorporating energy sharing and thermal comfort while considering HVs and hydrogen parking lots as critical assets:** The proposed model emphasizes optimizing energy sharing among prosumers, enabling efficient utilization of locally generated renewable energy. It also prioritizes the thermal comfort of prosumers by managing heating, ventilation, and air conditioning (HVAC) systems and other flexible loads. In addition, the model incorporates HVs and hydrogen parking lots as essential components. These parking lots not only facilitate the refueling of HVs but also contribute to energy storage and management within the community. This integration enhances the overall operational efficiency of the CEC, providing a flexible and resilient energy ecosystem that supports both sustainability and prosumer needs.
- **The traveling distance of HVs, modeled as a non-parametric uncertainty, is managed using the IGDT approach:** The behavior of HVs, including the distances they travel, is highly unpredictable due to various dynamic factors, such as driving habits, environmental conditions, and refueling availability. Instead of relying on fixed assumptions or historical data, the paper applies IGDT to model this uncertainty in a non-parametric manner. By leveraging IGDT, the model can make robust decisions that remain effective even under significant deviations in HV travel patterns.
- **The proposed model for the hydrogen parking lot can be viewed as community storage, where both hydrogen and electrical energy demands are met:** The hydrogen parking lot in this model is designed to act as a shared; energy storage system for the community. This dual capability of storing both hydrogen and electricity makes the parking lot a critical asset for balancing energy supply and demand within the CEC. It helps to ensure that the energy needs of prosumers whether in the form of hydrogen for refueling HVs or electricity for powering homes and businesses are consistently met.

2. The proposed framework

The proposed framework, depicted in Fig. 1, provides the proposed approach to manage the CEC with an emphasis on cost minimization. At the heart of this community is the energy community manager (ECM), whose primary role is to oversee the seamless integration of various energy resources. The CEC is embodied by a smart building comprising prosumers, individuals or entities who both produce and consume energy, equipped with rooftop photovoltaic (PV) panels.

These prosumers benefit from the capability to share surplus energy with one another, enhancing collective energy efficiency and self-sufficiency. The smart building is also outfitted with a sophisticated HVAC system that ensures comfortable indoor environments by the predicted mean Vvote (PMV) method, which dynamically adjusts to maintain the desired comfort levels based on occupants' feedback.

A distinguishing feature of this community is the inclusion of HVs owned by the prosumers. To support these vehicles, the ECM oversees a hydrogen parking lot, which functions as a refueling station and a critical component of the community's energy ecosystem. The hydrogen parking lot is equipped with an electrolyzer that produces hydrogen by consuming electricity sourced in two ways: from the solar panels installed by prosumers or through direct electricity purchases from the upstream power grid. The produced hydrogen can be either stored in a hydrogen storage tank for future use or immediately utilized by the HVs. Additionally, the stored hydrogen provides a versatile energy reserve that prosumers can convert back into electricity via fuel cells, further supporting the building's energy needs and enhancing grid independence.

The ECM utilizes IGDT to address uncertainty in HV travel distances, which are highly variable and difficult to predict due to dynamic user behaviors and varying operational conditions. IGDT, as a robust decision-making framework, enables the ECM to evaluate system performance under uncertain scenarios without requiring precise probabilistic information. Within this framework, the ECM can adopt two distinct attitudes: risk-averse or risk-seeking. In a risk-averse strategy, the ECM determines the maximum allowable variability in HV travel distances that the system can tolerate while maintaining operational cost. This conservative approach ensures reliable performance even under the worst-case conditions, where travel distances significantly deviate from expected values. Conversely, in a risk-seeking scenario, the ECM explores opportunities to maximize potential benefits, such as cost

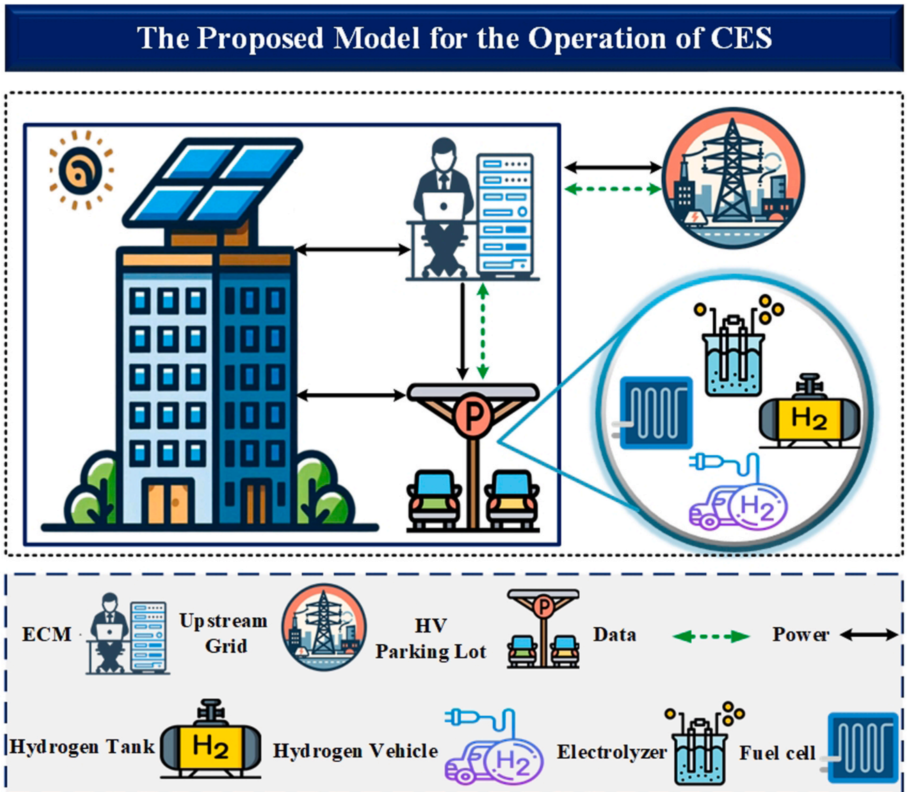

Fig. 1. Proposed model for CEC.

savings or performance improvements, under favorable conditions.

3. Optimization model

The optimization model is divided into two components: deterministic model and the uncertainty management using IGDT that are addressed in the first and second subsections, respectively.

3.1. Deterministic model

The objective function, which includes energy purchases and sales, considering the power needed for prosumers and the electrolyzer is shown in (1).

$$of = \min\left[\sum_{t=1}^{N_t}\left(\pi_t^{Buy,G}\left(P_t^{Buy,G} + P_t^{P2G,G}\right) - \pi_t^{Sell,G}P_t^{Sell,G}\right)\right] \tag{1}$$

$\pi_t^{Buy,G}$ and $\pi_t^{Sell,G}$ are the energy prices for purchasing from and selling to the grid, respectively. $P_t^{Buy,G}$, $P_t^{Sell,G}$ and $P_t^{P2G,G}$ are the power associated with buying from and selling to the grid and power purchased from the grid for the electrolyzer, respectively.

$$P_t^{Buy,G} = \sum_{m=1}^{N_m} P_{m,t}^{Buy,Pr} \tag{2}$$

$$P_t^{Sell,G} = \sum_{m=1}^{N_m} P_{m,t}^{Sell,Pr} \tag{3}$$

$$P_{min}^{Buy,G} \leq P_t^{Buy,G} \leq P_{max}^{Buy,G} \tag{4}$$

$$P_{min}^{Sell,G} \leq P_t^{Sell,G} \leq P_{max}^{Sell,G} \tag{5}$$

$$I_{m,t}^{Buy,Pr}P_{min}^{Buy,Pr} \leq P_{m,t}^{Buy,Pr} \leq I_{m,t}^{Buy,Pr}P_{max}^{Buy,Pr} \tag{6}$$

$$I_{m,t}^{Sell,Pr}P_{min}^{Sell,Pr} \leq P_{m,t}^{Sell,Pr} \leq I_{m,t}^{Sell,Pr}P_{max}^{Sell,Pr} \tag{7}$$

$$I_{m,t}^{Buy,Pr} + I_{m,t}^{Sell,Pr} \leq 1 \tag{8}$$

(2) and (3) represent prosumers' energy buying and selling. (4) and (5) ensure energy balance for consumption and surplus, while (6) and (7) set limits on energy transactions. (8) prevents simultaneous buying and selling of electricity. $P_{m,t}^{Buy,Pr}$ represents the power that each prosumer m buys from the grid, while $P_{m,t}^{Sell,Pr}$ is the power that each prosumer sells to the grid. P_{min} and P_{max} represent the minimum and maximum power limitation for each equation. I is a binary variable representing the state of the corresponding variable. The electrical load balance of prosumers is detailed in (9).

$$P_{m,t}^{Buy,Pr} - P_{m,t}^{Sell,Pr} + P_{m,t}^{self,PV} - \sum_{n=1}^{N_n} P_{m,n,t}^{Share} + P_{m,t}^{H2P} = P_{m,t}^{L} \tag{9}$$

$$P_{m,n,t}^{Share} = -P_{n,m,t}^{Share} \tag{10}$$

$$\sum_{t=1}^{N_t} P_{m,n,t}^{Share} = \sum_{t=1}^{N_t} P_{n,m,t}^{Share} \tag{11}$$

$$-P_{max}^{Share} < P_{m,n,t}^{Share} < P_{max}^{Share} \tag{12}$$

$$P_{m,t}^{L} = P_{m,t}^{BL} + P_{m,t}^{C} + P_{m,t}^{H} \tag{13}$$

Base on (9), $P_{m,t}^{self,PV}$ represents the part of PV generation consumed by each prosumer. $P_{m,n,t}^{Share}$ denotes energy sharing between prosumers m and n. $P_{m,t}^{H2P}$ is the power generated by the fuel cell. Power sharing between prosumers is addressed in (10) and (12). $P_{m,t}^{L}$ represents the power consumption for each prosumer, which includes fixed usage denoted by $P_{m,t}^{BL}$ and the HVAC power consumption for cooling $P_{m,t}^{C}$ and heating $P_{m,t}^{H}$, as defined by (13). Constraints on the HVAC system are outlined in (14)–(21).

$$\theta_{m,t+1} = e^{-\frac{\Delta T}{CR}}\theta_{m,t} + \left(1 - e^{-\frac{\Delta T}{CR}}\right)\left(\theta^{amb}_{m,t} - \theta^{T}_{m,t}\right) \tag{14}$$

$$\theta^{T}_{m,t} = R\eta^{T}_{m}\left(P^{C}_{m,t} + P^{H}_{m,t}\right) \tag{15}$$

$$I^{C}_{m,t}P^{C,min}_{m} \le P^{C}_{m,t} \le I^{C}_{m,t}P^{C,max}_{m} \tag{16}$$

$$I^{H}_{m,t}P^{H,min}_{m} \le P^{H}_{m,t} \le I^{H}_{m,t}P^{H,max}_{m} \tag{17}$$

$$I^{C}_{m,t} + I^{H}_{m,t} \le 1 \tag{18}$$

$$PMV_{m,t} = 2.43 - 3.76\left(\frac{\theta^{human} - \theta_{m,t}}{M(R^{cloth} + 0.1)}\right) \tag{19}$$

$$PMV_{min} \le PMV_{m,t} \le PMV_{max} \tag{20}$$

$$PMV_{m,1} = 0 \tag{21}$$

Here, $\theta_{m,t}$ represents the indoor temperature, and $\theta^{T}_{m,t}$ refers to the temperature modification by HVAC. R denotes thermal resistance, C is thermal capacitance, $\theta^{amb}_{m,t}$ represents the ambient temperature, η is the efficiency factor, θ^{human} is the average temperature of human skin in a comfortable state, R^{cloth} refers to the thermal resistance of clothing, and M is the human energy metabolism rate. The constraints related to hydrogen converters, storage units, and hydrogen vehicles are as follows:

$$H^{HE}_{t} = \sum_{m=1}^{N_m}\left(\frac{\eta^{P2H}\left(P^{P2G,PV}_{m,t} + P^{P2G,G}_{t}\right)}{\sigma_{HE}}\right) \tag{22}$$

$$P^{P2G,PV}_{m,t} + P^{self,PV}_{m,t} = P^{PV}_{m,t} \tag{23}$$

$$\sum_{m=1}^{N_m} P^{H2P}_{m,t} = H^{FC}_{t}\eta^{H2P}\sigma_{FC} \tag{24}$$

$$H^{HE}_{t} + H^{HES,dis}_{t} + \sum_{m=1}^{N_m} H^{HV,dis}_{t} = H^{FC}_{t} + H^{HES,ch}_{t} + \sum_{m=1}^{N_m} H^{HV,ch}_{t} \tag{25}$$

Hydrogen production by the electrolyzer, denoted by H^{HE}_{t}, depends on the electrical power used, as specified in (22). Power sources include the grid and solar panels, represented by $P^{P2G,PV}_{m,t}$, as stated in (23). σ_{HE} is the electrolyzer's efficiency coefficient. Hydrogen storage and conversion to electrical power via fuel cells are addressed in (24) and (25). H^{FC}_{t} represents hydrogen consumption by fuel cells, while $H^{HES,ch}_{t}$ and $H^{HES,dis}_{t}$ denote the amount of hydrogen charged and discharged from the Hydrogen Energy Storage (HES) system. Additionally, $H^{HV,ch}_{t}$ and $H^{HV,dis}_{t}$ represent the hydrogen used for charging and discharging HVs.

$$SOC^{HES} = SOC^{HES}_{t-1} + H^{HES,ch}_{t}\eta^{HES} - H^{HES,dis}_{t}\Big/\eta^{HES} \tag{26}$$

$$SOC^{HES,min} \le SOC^{HES} \le SOC^{HES,max} \tag{27}$$

$$I^{HES,ch}_{t}H^{HES,chmin} \le H^{HES,ch}_{t} \le I^{HES,ch}_{t}H^{HES,chmax} \tag{28}$$

$$I^{HES,dis}_{t}H^{HES,dismin} \le H^{HES,dis}_{t} \le I^{HES,dis}_{t}H^{HES,dismax} \tag{29}$$

$$I^{HES,ch}_{t} + I^{HES,dis}_{t} \le 1 \tag{30}$$

$$SOC^{HV}_{m} = SOC^{HV}_{m,t-1} + H^{HV,ch}_{m,t}\eta^{HV} - H^{HV,dis}_{m,t}\Big/\eta^{HV} - H^{Con}_{m,t} \tag{31}$$

$$SOC^{HV,min} \le SOC^{HV}_{m} \le SOC^{HV,max} \tag{32}$$

$$I^{HV,ch}_{m,t}H^{HV,chmin} \le H^{HV,ch}_{m,t} \le I^{HV,ch}_{m,t}H^{HV,chmax} \tag{33}$$

$$I^{HV,dis}_{m,t}H^{HV,dismin} \le H^{HV,dis}_{m,t} \le I^{HV,dis}_{m,t}H^{HV,dismax} \tag{34}$$

$$I^{HV,ch}_{m,t} + I^{HV,dis}_{m,t} \le 0 \nabla D_{m,t} \ne 0 \tag{35}$$

$$I^{HV,ch}_{m,t} + I^{HV,dis}_{m,t} \le 1 \nabla D_{m,t} = 0 \tag{36}$$

$$H^{con}_{m,t} = \varphi_{m,t}D_{m,t} \tag{37}$$

The HES system's State of Charge (SoC) is governed by (26), with charging and discharging limits outlined in (27)-(30). HV storage and usage constraints are detailed in (31)-(34), with (35) and (36) restricting charging and discharging during vehicle operation. Hydrogen consumption, represented by $H^{con}_{m,t}$, relative to vehicle distance, denoted by $D_{m,t}$, is described in (37). $\varphi_{m,t}$ is the efficiency coefficient of HV consumption.

3.2. IGDT optimization model

IGDT offers a robust framework for addressing challenges associated with uncertain input data, avoiding reliance on traditional probabilistic or possibilistic methods. The approach can be formulated using the following optimization model:

$$\min \text{function}(\psi, \omega) \tag{38}$$

$$h(\psi, \omega) = 0 \tag{39}$$

$$g(\psi, \omega) \le 0 \tag{40}$$

In this model, function(ψ, ω) represents the cost function targeted for minimization, with ψ as the decision variables and ω as the uncertain parameters impacting the system. In the context of IGDT, an uncertainty model for a parameter ω, represented as U, is characterized by an unbounded collection of nested sets.

$$U(\omega, \alpha) = \{\omega : |\omega - \widetilde{\omega}| \le \widetilde{\omega}\alpha\}, \alpha \ge 0 \tag{41}$$

In the given equation (41), the variable u signifies the uncertain parameter, whereas $\widetilde{\omega}$ denotes the forecasted variable. Furthermore, α is described as the uncertainty horizon. IGDT can be applied from either a risk-averse or risk-seeking standpoint. In the risk-averse application of IGDT, the decision-maker is content if the cost does not exceed a predetermined critical value. The objective in this risk-averse IGDT model is to maximize the uncertainty horizon, also known as the robustness horizon. This approach ensures that any variation in uncertain input data, within the defined robustness set, results in a cost that is no greater than the critical cost. The formulation for a risk-averse IGDT-based model is presented as follows:

$$\max \alpha(\psi, \omega) \tag{42}$$

$$\text{function}(\psi, \omega) \le of^{cr} \tag{43}$$

$$of^{cr} = (1 + \beta)of^{*} \tag{44}$$

$$h(\psi, \omega) = 0 \tag{45}$$

$$g(\psi, \omega) \le 0 \tag{46}$$

In a risk-averse IGDT approach, the objective is maximized the robustness horizon, while f^{*} represents the nominal optimal cost, achieved when uncertain input data align with the forecasted values. The term f^{cr} refers to the maximum tolerable cost, known as the critical cost. β acts as a critical cost deviation factor. Essentially, the primary objective in risk-averse IGDT is to configure the decision variables such that they protect the decision-maker from the adverse impacts of deviations in uncertain input data. In essence, risk-averse IGDT ensures that minimum requirements are met. Notably, lower critical cost values result in smaller robustness horizons, highlighting the sensitivity of the model to cost thresholds.

In its risk-seeking application, IGDT focuses on maximizing potential gains by exploring decisions that perform well under the most favorable scenarios. For risk-seeking, the best possible scenario is achieved at the minimum uncertainty horizon. The 'opportunity horizon' refers to the level of uncertainty where the decision yields a favorable outcome, such as meeting or exceeding the target cost of^{trg}. This approach contrasts with the risk-averse application of IGDT, which prioritizes minimizing potential losses. By determining both the decision variables and the extent of uncertainty (opportunity horizon), IGDT aims to leverage favorable conditions, effectively balancing robustness and opportunity-seeking in uncertain environments.

$$\min \alpha(\psi, \omega) \tag{47}$$

$$\text{function}(\psi, \omega) \leq of^{trg} \tag{48}$$

$$of^{trg} = (1-\beta)of^{*} \tag{49}$$

$$h(\psi, \omega) = 0 \tag{50}$$

$$g(\psi, \omega) \leq 0 \tag{51}$$

The optimistic decision-maker in a risk-seeking scenario aims to capitalize on favorable deviations of uncertain input data from their predicted values. As the target cost of^{trg}, is set lower, the required opportunity horizon decreases accordingly. This reflects the strategy of leveraging positive uncertainties to enhance outcomes.

3.3. Hydrogen vehicles uncertainty modeling by the IGDT approach

The IGDT provides a robust framework for tackling modeling challenges posed by uncertain input data, distinguishing itself by eschewing traditional probabilistic and possibilistic methods. In this paper, the traveled distance of the HVs has been modeled by the IGDT approach. The risk-averse and risk-seeker models attitudes of the IGDT approach are as follows:

3.3.1. Risk-averse IGDT optimization model for CECs

This paper introduces a risk-averse IGDT-based model for HVs in CECs that focuses on maximizing the robustness horizon. The model is demonstrated as follows:

$$\max \alpha \tag{52}$$

$$\sum_{t=1}^{N_t} \left(\pi_t^{Buy,G}\left(P_t^{Buy,G} + P_t^{P2G,G}\right) - \pi_t^{Sell,G} P_t^{Sell,G}\right) \leq of^{cr} \tag{53}$$

$$of^{cr} = (1+\beta)of^{*} \tag{54}$$

$$H_{m,t}^{con} = \varphi_{m,t}(1+\alpha)D_{m,t} \tag{55}$$

Subject to constraints (2)–(37).

This approach ensures that the operation costs of CECs do not exceed a predetermined critical or acceptable level as shown in (53). By constraining the operation costs to stay within the target under the worst-case scenario of uncertain input data, the model effectively safeguards against cost overruns, providing a reliable financial buffer for CEC operations. To accurately model the worst-case scenario regarding the distance a HV can travel, the term $(1+\alpha)$ is incorporated into (37). This modification is designed to account for the maximum potential deviation in travel distance. By making this adjustment, the model provides a safeguard for the ECM against adverse variations in the performance of HVs.

3.3.2. Risk- seeking IGDT optimization model for CECs

This subsection introduces a risk-seeking IGDT-based model designed for ECM, which minimizes the opportunity threshold necessary to achieve the target cost.

$$\min \alpha \tag{56}$$

$$\sum_{t=1}^{N_t} \left(\pi_t^{Buy,G}\left(P_t^{Buy,G} + P_t^{P2G,G}\right) - \pi_t^{Sell,G} P_t^{Sell,G}\right) \leq of^{trg} \tag{57}$$

$$of^{trg} = (1-\beta)of^{*} \tag{58}$$

$$H_{m,t}^{con} = \varphi_{m,t}(1-\alpha)D_{m,t} \tag{59}$$

Subject to constraints (2)–(37).

The risk-seeking IGDT model is presented, where the minimum opportunity horizon is identified to ensure that a specific target operation cost can be met. To achieve this target operation cost, the operational cost must be less than or equal to the target operation cost. Therefore, a reduction factor $(1-\alpha)$ is incorporated into equation (37) to model the optimal scenario for uncertain parameters. This adjustment ensures the model captures the best possible outcome under uncertainty, facilitating the achievement of ECM's financial objectives.

4. Numerical study

The Mixed-Integer Linear Programming (MILP) problem, is solved using the CPLEX solver within the GAMS environment. A computer equipped with an i7-10750H processor and 16 GB of RAM was used to solve the problem. The computational time was 6 s, demonstrating the practical applicability of the proposed model for large CECs with numerous prosumers. The model is executed over a full year, analyzing each season individually to assess its performance. To highlight the model's capability under peak demand conditions, a 24-h simulation is conducted for July 15, a representative day in summer with high demand.

4.1. Input data

The CEC includes a smart building with five prosumer units, each having rooftop solar panels, HVs, and energy-sharing capabilities. The HVAC system ensures thermal comfort, while a dedicated HV parking lot features an electrolyzer, fuel cell, and hydrogen storage. The building's optimal operation is managed by an ECM. The average baseload of the CEC, the electricity purchase and sale prices throughout the year, and the average total PV generation, along with the temperature data for one year, are presented in the supplementary materials of the paper. The parameters associated with the HVAC system have also been taken from Ref. [15]. The necessary parameters for the CEC's optimal operation are sourced from Ref. [44], with electrolyzer and fuel cell parameters from Ref. [45]. The HVs used are Hyundai NEXO models [46].

4.2. One year's results

The annual operating costs of the CEC, as analyzed seasonally in Table 2, show that winter has the highest cost (36.37%) due to increased heating demand and reduced PV generation. Spring has the lowest cost (18.22%) due to mild temperatures and improved PV output. Summer accounts for 21.12%, driven by cooling demands, partially offset by high PV generation. Autumn's cost is 24.28%, reflecting balanced heating and cooling needs with declining PV output. These results highlight the influence of temperature and daylight on seasonal energy costs.

Fig. 2 shows the seasonal power buying patterns of the CEC, with

Table 2
Operation cost seasonal result.

Seasons	Operation cost ($)	Percentage of total
Winter	2419.30	36.37%
Spring	1211.97	18.22%
Summer	1404.65	21.12%
Autumn	1615.08	24.28%
Total operation cost	6651.01	100%

peaks in winter due to high heating demands and reduced PV generation. Power purchases drop in spring due to milder temperatures and increased PV output. In summer, cooling needs cause a moderate rise, but high solar generation offsets costs. Autumn shows balanced heating and cooling demands, with reduced PV output slightly increasing grid reliance. These patterns highlight the need for optimized energy management to balance local generation and grid purchases across seasons.

Fig. 3 illustrates seasonal HVAC power consumption and indoor temperatures. Winter has the highest consumption (18,000 kW, 34%) due to heating demands to maintain comfort. Spring sees a significant drop (10,000 kW, 19%) with minimal heating or cooling needs. Summer consumption rises to 12,000 kW (22%) for cooling, offset by high PV generation. Autumn's usage is 13,000 kW (25%), balancing heating and cooling demands. These trends show the influence of seasonal temperatures on HVAC energy consumption.

Fig. 4 shows seasonal hydrogen production variability. Winter has the lowest production (15%) due to reduced solar irradiance and high heating demands limiting surplus electricity. Production increases in spring (25%) with milder temperatures and higher PV output. Summer peaks at 35% due to maximum solar availability, despite increased cooling demands. In autumn, hydrogen production declines to 25% due to reduced PV generation and moderate energy demands. This seasonal distribution aligns with HV travel distances, ensuring consistent fuel availability. The IGDT-based framework optimizes hydrogen production, enhancing energy resilience and sustainability despite seasonal variations.

Fig. 5 depicts the electrical power output from the fuel cell, highlighting seasonal variations in production. In winter, fuel cell power generation is significantly lower due to the reduced hydrogen availability, resulting from decreased electrolyzer activity during this season when solar irradiance is limited. Consequently, less hydrogen is stored, limiting the fuel cell's ability to generate power. Conversely, in summer, the fuel cell's power output is markedly higher. This increase is driven by the greater hydrogen production from the electrolyzer, fueled by higher solar panel output. The stored hydrogen is then efficiently converted into electrical power during peak load hours, particularly when electricity demand peaks in summer. This strategic utilization of stored hydrogen in summer ensures that the increased electricity demand is met effectively, demonstrating the fuel cell's pivotal role in maintaining energy balance within the community.

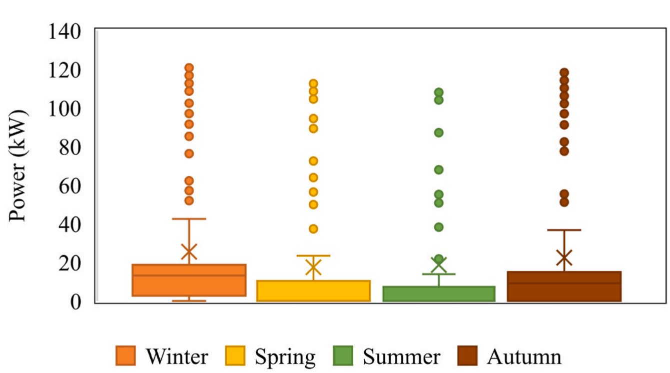

Fig. 2. Seasonal CEC power buying over one year.

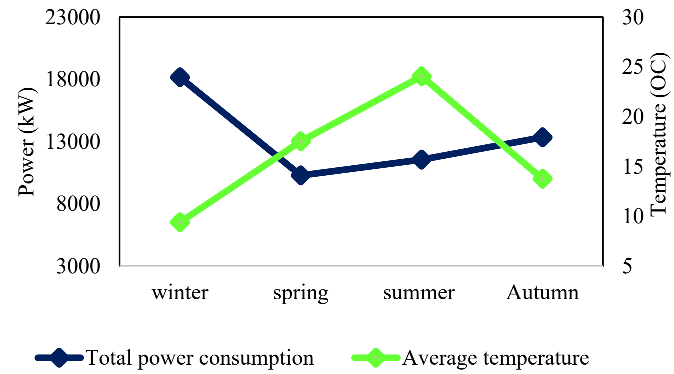

Fig. 3. Seasonal HVAC performance and average outdoor temperature of the CEC over one year.

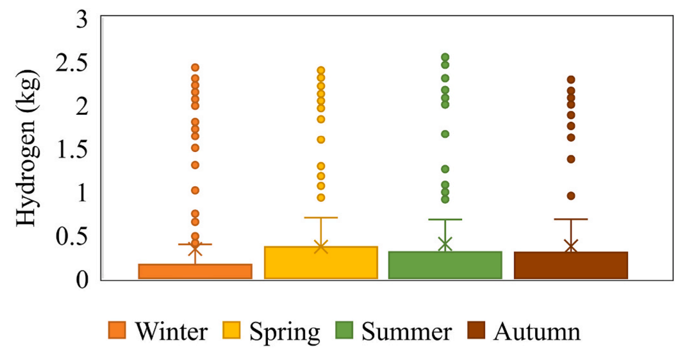

Fig. 4. Seasonal hydrogen produce over one year.

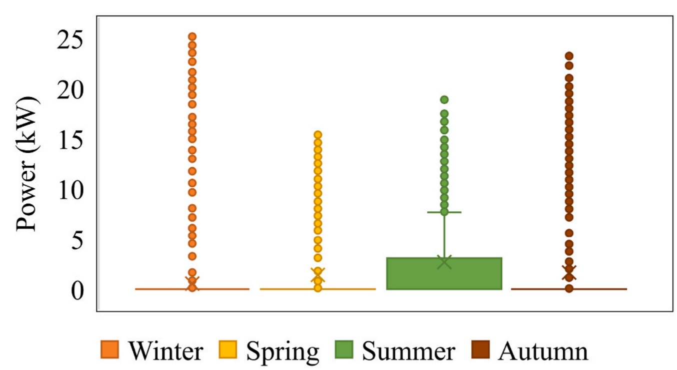

Fig. 5. Seasonal Power produce by fuel cell over one year.

4.3. Daily operation results

The results of the optimal operation for the CEC over a 24-h period during the annual peak load, which occurs on July 15, are shown in Fig. 6. This figure illustrates the power purchased from the grid by the CEC. The results indicate that in the early hours, when electricity prices are relatively low, the ECM purchases large amounts of power from the grid.

As the day progresses and photovoltaic production increases, there is a significant reduction in grid purchases, aligning with higher daytime electricity prices and encouraging reliance on locally generated energy. Despite the high solar output, the community does not sell significant power to the grid; instead, the ECM converts the excess power into hydrogen using an electrolyzer (As shown in Fig. 7) and stores it in the storage tank. In the evening, as solar production declines and electricity prices rise, the manager converts the stored hydrogen back into

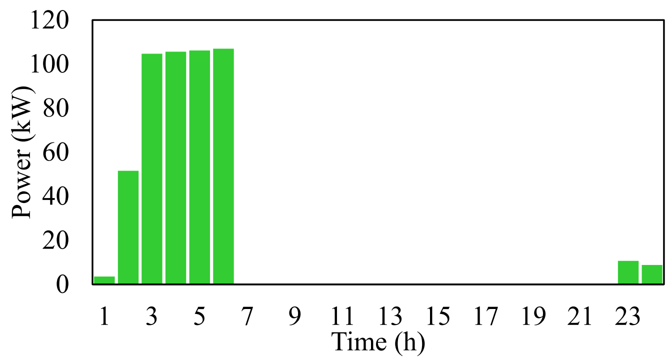

Fig. 6. The power exchange with the upstream network.

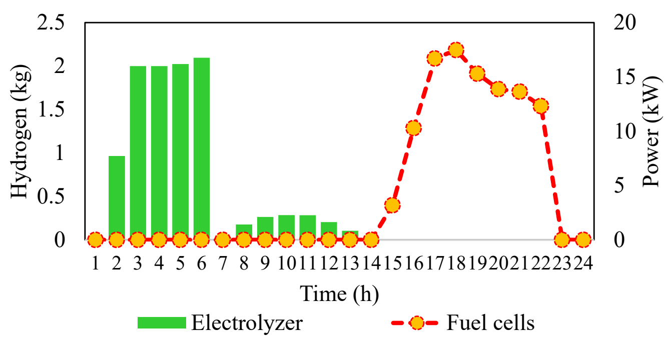

Fig. 7. The performance of Electrolyzer and Fuel cells.

electricity via fuel cells to meet the community's power needs. In the final hour, the community purchases additional power to meet demand, highlighting the challenge of managing costs and balancing consumption with the availability of renewable resources.

Fig. 7 illustrates the operational strategy of the electrolyzer and fuel cells throughout the day in the proposed CEC. During the early hours, the electrolyzer converts electricity purchased from the grid into hydrogen, taking advantage of lower electricity prices. This conversion activity peaks around 6:00 a.m., coinciding with the most favorable grid prices. As solar PV generation increases during the day, the electrolyzer's operation diminishes, prioritizing the use of surplus PV energy to either meet the immediate needs of the community or to be converted into hydrogen for storage, rather than exporting the excess to the grid. In the late afternoon and evening, when solar output declines and both electricity demand and prices rise, the stored hydrogen is utilized by fuel cells to generate electricity, with peak operation occurring between 4:00 p.m. and 8:00 p.m. This strategy reflects an optimal operational approach for the CEC, balancing generation, storage, and consumption to maximize economic and energy efficiency.

The performance and dynamics of both processes, including the allocation of hydrogen to vehicles and storage management, are depicted in Figs. 8 and 9. This strategy not only enhances the flexibility of the energy system but also optimizes the use of renewable resources within the community.

As shown in Figs. 8 and 9, in the early hours, the ECM purchases low-cost electricity and converts it into hydrogen, which is primarily used for charging HVs, with any excess stored in the hydrogen tank, as indicated by the SOC. As the day progresses and solar panels generate electricity, surplus energy is also converted into hydrogen and stored, especially when vehicles are away during working hours. In the late afternoon and evening, when electricity demand and prices peak, the stored hydrogen is discharged to generate electricity, reducing reliance on expensive grid power. Fig. 9 illustrates that HVs typically leave the parking lot in the morning and return later in the day, aligning with daily routines. This

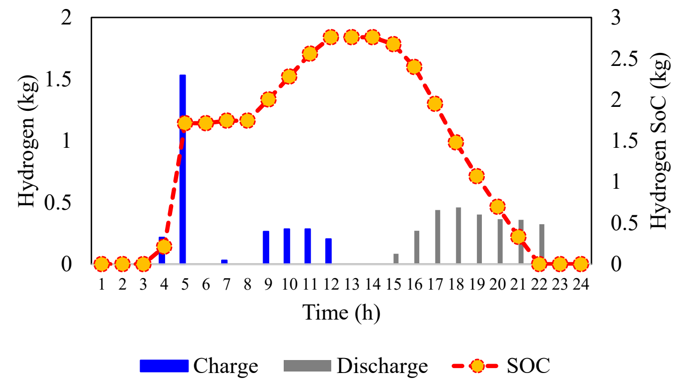

Fig. 8. The performance of the hydrogen tank.

flexible vehicle usage complements the CEC's strategy of utilizing stored hydrogen during peak demand periods, optimizing energy costs, and enhancing system resilience.

4.4. IGDT results

This study applies IGDT for a peak day in the summer to examine the impact of uncertainty during peak load conditions. Additionally, the study operates under the assumption that the distance traveled by each HV is forecasted one day in advance. To address the inherent uncertainties in these travel predictions, the IGDT framework is employed to model and analyze the potential deviations.

4.4.1. Risk-averse strategy result

Fig. 10 presents the relationship between the robustness horizon of HV travel distances and various critical operation cost deviation factors. The figure demonstrates a steady, linear growth in the robustness horizon as the critical cost deviation factor increases from 0 to 0.8. At a 0% deviation factor, the robustness horizon is nearly zero, indicating no allowance for any deviation in travel distance without incurring additional expenses. As the deviation factor increments from 0.1 to 0.8, the robustness horizon proportionally expands, with each 10% increase in the critical cost deviation factor corresponding to approximately a 12.5% expansion in the robustness horizon for HV travel distances.

When the critical cost deviation factor reaches 40%, the robustness horizon extends to 50%. This means the system can tolerate up to a 50% variability in travel distance within this deviation level without exceeding the critical cost limit. At an 80% deviation factor, the robustness horizon grows to about 100%, effectively doubling the permissible variability in travel distance compared to the 40% deviation factor. This linear trend underscores that the system's ability to accommodate variations in HV travel distances is directly and proportionally tied to the critical cost deviation factor, offering greater flexibility in managing uncertainties as the deviation factor increases.

Overall, this figure emphasizes the significance of selecting appropriate critical cost deviation factors. Higher deviation factors substantially enhance the robustness horizon, thereby increasing the system's capacity to manage uncertainties in travel distances while keeping costs within acceptable ranges.

4.4.2. Risk-seeking strategy result

To model the system using a risk-seeking approach for managing the uncertainties related to HV travel distances, the critical operation cost deviation factors are varied within a range of 0–1. The opportunity-based objective function is then optimized while adhering to the specified constraints. The results indicate that the minimum deviation from the forecasted HV travel distances is sufficient to achieve costs that remain below the target threshold.

Fig. 11 in this study illustrates how the opportunity horizon for HV

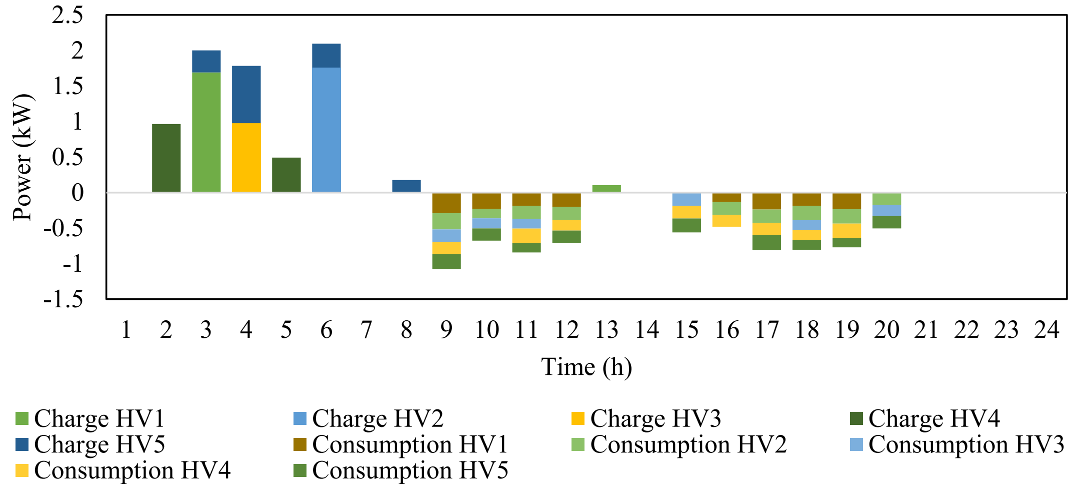

Fig. 9. The performance of HVs.

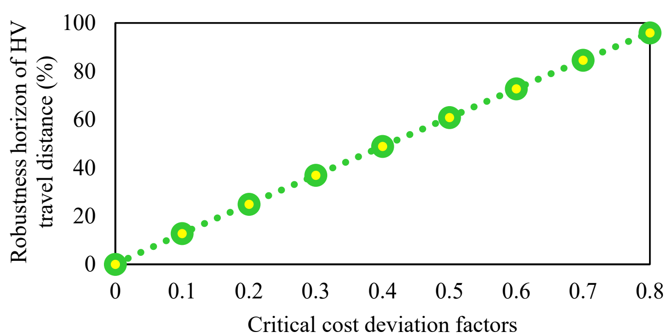

Fig. 10. Robustness horizon of HV travel distance for different critical operation cost deviation factors.

travel distances varies with different critical operation cost deviation factors under a risk-seeking strategy. At a deviation factor of 0% (0), the opportunity horizon begins at approximately 0%, aligning with the risk-neutral scenario where the critical cost matches the deterministic cost. As the critical cost deviation factor rises, the opportunity horizon correspondingly broadens. For example, when the deviation factor is 0.5 (50%), the opportunity horizon reaches about 60%, meaning the system can handle up to a 60% variation in travel distances without exceeding the target cost threshold. This trend indicates that each 10% increment in the critical cost deviation factor is associated with roughly a 10% increase in the opportunity horizon, up until the deviation factor approaches 0.7 (70%). Beyond this point, the graph levels off, with the opportunity horizon stabilizing between 90% and 100%. This plateau

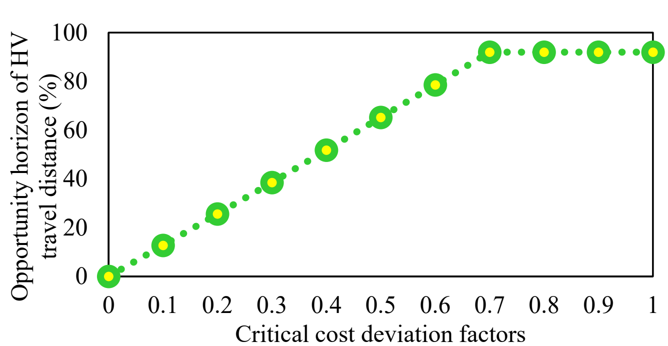

Fig. 11. Opportunity horizon of HV travel distance for different critical operation cost deviation factors.

suggests that further increases in the deviation factor beyond 0.7 do not significantly extend the opportunity horizon.

5. Real-world applications of the proposed framework

Hydrogen is crucial for sustainable energy, offering zero emissions and supporting renewable energy storage in CECs. This study highlights HVs as key to decarbonizing transportation and enabling energy storage and sharing within CECs. Using IGDT, it models HV user behavior to optimize energy management and reduce operational costs. According to the obtained results, the main aspects of the real-world applications are summarized as follows:

- The model emphasizes storing surplus solar energy as hydrogen during summer. This directly addresses the real-world challenge of managing excess PV generation and reduces reliance on grid power during peak cooling periods.
- By converting low-cost electricity into hydrogen during off-peak hours, the model aligns with real-world efforts to reduce energy expenses and manage storage for use during high-price periods.
- Seasonal HVAC energy use patterns allow CECs to balance heating and cooling demands efficiently, reducing costs while maintaining indoor comfort, and directly improving energy management in varying climates.
- The model's ability to accommodate up to 60% variability in HV travel distances under risk-seeking strategies ensures practical HV adoption, addressing uncertainties in user behavior often faced in real-world mobility planning.

6. Conclusion

This study introduces a robust framework based on IGDT to address uncertainties in driving and refueling behaviors, ensuring seamless and efficient integration of HVs within community hydrogen parking lots. These findings have practical implications for policymakers and energy community managers, particularly in designing adaptive and cost-effective systems that align with energy transition goals. The proposed model enables energy management by storing surplus solar energy as hydrogen, optimizing off-peak electricity use for cost-effective storage, balancing seasonal HVAC demands, and addressing uncertainties in hydrogen vehicle usage to support real-world mobility and energy challenges. The obtained results demonstrate seasonal variations in operational costs and highlight actionable strategies to optimize performance. Winter incurs the highest costs at 36.37 % due to heating demands and reduced PV generation, whereas spring benefits from milder temperatures and higher solar output, resulting in the lowest costs at 18.22 %. The IGDT-based framework equips energy community managers with the tools to withstand variability in HV usage patterns. Under risk-averse strategies, the system tolerates up to 50 % variability in travel distances without exceeding cost thresholds, while risk-seeking strategies allow for even greater flexibility with 60 % variation. This study's IGDT-based approach uses simplified assumptions about hydrogen vehicle user behavior. Future research should develop advanced behavioral models and transition from day-ahead operations to real-time algorithms for improved accuracy, responsiveness, and efficiency. Moreover, future research could explore peer-to-peer negawatt trading to optimize energy exchanges and promote sustainable, equitable, and participatory energy systems.

CRediT authorship contribution statement

Homayoun Ghasemnejad: Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **Sobhan Dorahaki:** Writing – review & editing, Validation, Software, Resources, Methodology, Investigation, Conceptualization. **Masoud Rashidinejad:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Formal analysis, Conceptualization. **S.M. Muyeen:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijhydene.2024.12.500.

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