Received: 8 October 2021 | Revised: 8 April 2022 | Accepted: 23 April 2022

IET Generation, Transmission & Distribution

DOI: 10.1049/gtd2.12500

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

A novel energy management framework incorporating multi-carrier energy hub for smart city

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Abstract

The development of advanced and intelligent measurement instruments in recent years has increased the intelligence of modern energy systems, especially power systems. Besides, with the advancement of energy conversion technologies, these systems benefit from multi-carrier energy resources. Accordingly, this paper presents a model of smart city which considers various components, including smart transportation system (STS), microgrid (MG), and smart energy hub (SEH) with the ability of energy transformation. The proposed model addresses the islanded operation of a smart city that makes it a smart island. This island deploys the energy carriers of electricity, heat, gas and water as well. In addition, STS includes electric vehicle (EV) parking lots as well as metro system (MS) that can interactively exchange energy. More precisely, the different components of the smart island are modelled on the assumption of energy interdependency. In the proposed model, the water supply unit in SEH is provided which can be effective in reducing the cost of components by supplying water to them. In order to exchange energy within STS, metro stations have been optimally allocated using intelligent water drops (IWD) optimization method. In addition to smart island modelling, this paper quantifies the uncertainties within STS and MG using cloud theory. Eventually, the proposed model is simulated to ensure its effectiveness and accuracy.

1 | INTRODUCTION

1.1 | Aims and scope

In the contemporary world cities are getting bigger and more populated. According to the statistics, about ten billion people or 70% of the world population are expected to live in cities throughout the world by 2050 [1, 2]. It seems as a major challenge to deal with massive needs of future communities. Therefore, it is predictable that almost all cities will be faced with major challenges such as economic development, lessening emissions, energy efficiency, and effectively harnessing the distributed energy resources (DERs), to name a few. These challenges each appears to be an obstacle on the way to sustainable development. Fortunately, in the last decade, a new concept known as smart city is developed, which makes us able to constructively cope with above mentioned challenges. There exist several descriptions for smart city, however, all of them have some main features in common. In fact, various descriptions verify that a smart city utilizes multilateral communications between sensors as well as benefits from integrated and connected infrastructures to improve the welfare of residents [1, 3–5]. Moreover, smart cities have the ability to optimize the use of integrated sources of energy [6]. This, basically, takes place on the Internet of Things (IoT) framework. Fitted with the IoT technology, all elements present in the smart city can communicate and interact with others which means that every single element can plays a role in the energy management of the whole system [7]. This, along with similar capabilities of such systems, makes its management really complex and difficult, thus necessitating the automation and smart control of the system [1]. Therefore, since the energy and water facilities are vitally important to sustainability of cities among six key dimensions of smart cities [3], this work focuses on smart energy management of a water and energy hub.

1.2 | Background

Smart cities have attracted numerous researchers' attention in recent years. The main reason of that lies behind the necessity of finding novel solutions for extensive challenges that future cities will be likely to face with. With this in mind, researchers have been trying to develop their ideas upon different aspects of the smart city. In this way, some recent works that more focus on smart energy management are outlined here to provide better understanding from what have been done so far.

To begin with, smart cities consist of different components that closely work together. The two major part of the smart city include the smart grid (SG) and smart transportation system (STS). The former is made up of different components such as smart buildings, microgrids, storages, and distributed and renewable energy resources, while the latter encompasses the metro system (MS) and electric vehicles (EVs) [1, 3]. These heterogeneous elements and the synergies between them impose both challenges and opportunities on smart cities that should be addressed in its energy management. It should be noted that STS puts a huge amount of electric demand on the smart grid as both electric trains (ETs) and geographically distributed EVs massively consume electric energy. On the other hand, the elements of transportation system can effectively support the smart grid by feeding energy to the grid [8, 9]. More specifically, the intermittent behaviour of renewable energy sources (RESs) causes energy shortage during some periods of a day. Therefore, the elements of transportation system, as a promising solution, can productively contribute to the balance between generation and consumption of the whole grid [1, 10]. This usually takes place through vehicle-to-anything (V2X) and anything-to-vehicle (X2V) technologies [8, 11, 12], and is mainly due to the emergence of high technology batteries [13]. It is worth nothing that EV-related technologies have some strengths and weaknesses that all described by authors in [14, 15]. Furthermore, authors in [16] comprehensively discussed the potentials of STS in a smart city. An IoT-based approach for distributional coordination of STS and SG is proposed in [17] to provide smart city with a holistic framework. Considering the importance of efficient operation of STS, researchers in [18] developed several tasks to boost power and driving efficiency as well as to beneficially harvest the regenerative braking energy (RBE). To provide better understanding, RBE appears to be the most efficient way of improving the performance of STS as it can be simply obtained via traction motors installed on ETs [1, 19]. In fact, this type of motors has the ability to reproduce the energy while ETs are decelerating [13]. RBE can be consumed by EVs in a real-time manner provided that the availability of ETs, that is, arrival and departure times is specified or optimally scheduled [20]. More efficiently, it is crucial to coordinate energy storages systems or EVs parking lots and RBE which is the scope of the author's works in [19]. This helps the system to ignore the complexity of scheduling but escalating the costs [21].

In 2007 a concept of energy hub (EH) was introduced to the field of energy management with the aim of modelling and analyzing multi-carrier energy systems (MCESs) [22]. The foundation of this concept appears to be the interdependent operation of power and water grid, gas network, and heating systems [9, 23, 24]. This naive concept has been considerably developed by the evolution of more advanced measuring devices. In fact, development of intelligent devices, emerges a novel concept so-called smart energy hub (SEH) whose aim is to optimally coordinate the number of different forms of energy within integrated systems like smart cities [22]. In general, SEH consists of three key parts including (a) multi-energy storage systems, (b) conversion units which allow SEH to convert electricity, gas, and heat to each other, although very pricy to transform some energy forms such as electricity power to gas (c) and obviously inputs and outputs [23]. Since the first purpose of modelling EHs is to optimally operate multi-energy systems, some works try their best to integrate EHs and optimize energy networks [9, 23–25]. From the operator's perspective, aggregated energy management of a network of EHs is more capable of flexibility compared to individually management of an EH [26]. An innovative and robust method to model interconnected SEHs is proposed in [25]. Some studies conducted a survey of the role of combined heat and power (CHP) units as well as EVs on EHs, similar to what authors have done in [27]. A comprehensive and practical framework for smart MCESs considering transportation systems and associated traffic flow is presented in [9]. MCESs is claimed to have a lot to offer to smart city, because of the reliable, environmentally-friendly and cost-efficient energy services delivery [26]. As mentioned before, there are synergies between SEHs as the vital components of MCES, and other components in the smart city. This is addressed and focused by authors in [24].

Besides many advantages of SEHs including emission reduction, flexibility and reliability improvement as well as simultaneously providing users with different carriers [23, 28], there exist several drawbacks in the wide use of such systems. On top of all, the cost of implementation and operation of SEHs is noticeably high. This necessitates the adoption of verified optimization methods [22, 29]. Furthermore, the wide use of IoT-based communication as well as high penetration of renewable-based generation, escalate the risk of cyber-attack and malicious activity throughout the system [30], thus showing the importance of cyber security considerations, for example, the role of blockchain technology in intelligent transportation [31].

The focus of this research paper is more on the island mode operation of RES-based microgrid. It is noteworthy to address some related research works, although, to the best of the authors' knowledge, the existing literature fails to propose an optimal model for islanded microgrids incorporating SEH and STS. Authors in [22] surveyed the integration of distributed energy resources (DERs) such as demand response and storages into SEHs. In [32] writers stepped forward with a framework for islanded mode MCESs based on DERs. Using deep learning algorithms for demand response (DR) as the most

FIGURE 1 The schematic smart island

favourable type of DERs, authors in [33] proposed a smart approach to manage the energy of a smart city. Furthermore, some researchers have studied the optimized operation of combined energy hubs considering RESs and DRs [34]. The proposed model is tried to provide optimal efficiency and cost by forming a proper structure for EHs. The study in [35] is devoted to smart island where a stochastic energy management model for MCES is introduced. This model considers reinforcement machine learning method to optimize the operation. Similarly, the deep reinforcement learning algorithm is utilized by writers in [36] to optimally schedule MCESs from prosumers' viewpoint.

1.3 | Features and capabilities

Considering the above literature review, it is safe to say that the operation of a smart island deserves more consideration in terms of modelling and optimizing the multi-carrier exchanges. In addition to electricity, gas and heat, water demand should be addressed in order to develop a comprehensive model of smart islands and capture the possibility of sea water adoption. The model also considers the potential source of electricity in she, that is, EVs and RBE which both are provided by STS. However, the allocation of EVs' parking lots and metro station is a bit challenging and need to be performed using a proper optimization method [37]. Figure 1 illustrates the graphical model of smart island.

This paper utilizes intelligent water drops (IWDs) algorithm as a novel and effective method to allocate aforementioned stations within the smart city. Moreover, the cloud theory (CT) is employed here to capture the uncertainties associated with different components of the smart city. Therefore, the authors of this paper have made three main contributions to the research filed as outlined below:

- A comprehensive model of a smart island considering the financial and energy exchanges between all components is proposed. As stated, Smart Island refers to a system being operated in stand-alone mode that easily accesses water sources.
  - Given the fact that the island accesses water, the model considers multi-carrier exchanges including electricity, heat, gas, and water to propose an integrated management of MCESs using SEH concept.
- The intrinsic uncertainty of the system, especially when it comes to the intermittent output of RESs and the unpredictable behaviour of STS's elements, has been tried to be taken into consideration via cloud theory, as an advanced method with the ability of converting qualitative parameters into quantitative ones.

1.4 | Paper organization

The rest of the paper is organized as follow: the model of the smart island is proposed in Section 2, while the stochastic framework based on cloud theory is described in Section 3. Section 4 is devoted to how the problem is solved by IWDs algorithm. In Sections 5 and 6, the simulation of the model and some remarks as a conclusion are presented, respectively.

2 | MATHEMATICAL FORMULATION OF SMART ISLAND

As mentioned earlier, this section is devoted to the development of mathematical formulation for the smart island and its transactions. It is noteworthy that this paper considers the multi-carrier energy exchanges of STS and microgrids (MGs). These transactions include vehicles to metro and microgrids (V2M & V2MG), as well as metro to microgrids and hubs (M2MG & M2H). Additionally, the transactions within STS, metro to vehicles (M2V), is addressed by the proposed model. The models and their limits of the above modes are defined in the following.

2.1 | The definition of M2MG

The M2MG technology enables metro system to sell the surplus energy obtained from RBE to the grid and make profit for the metro owner. Conversely, the metro system can fulfil the required amount of energy by purchasing that from the grid. Here the profit of MS equals to the profit it makes through M2MG minus the cost of technology establishment. This net profit can be calculated by (1) where the two profit and cost terms are computed by (2) and (3), respectively. The constraint demonstrated by Equation (4) guarantees the daily energy balance of MS. As the total RBE produced by MS is limited, it is necessary to meet the constraint of Equation (5).

- Objective functions

$$Profit_{M2MG} = Profit_{MMG} - cost_{MGM} \tag{1}$$

$$Profit_{MMG} = \sum_{n,t} \left(B2^n_{i,t} . P^{M2MG}_{n,t} \right) \quad \forall n \in \mho^n, t \in \mho^t \quad (2)$$

$$cost_{MGM} = \sum_{s,t} \left(B2^n_{i,t} . P^{MG2M}_{n,t} \right) \quad \forall n \in \mho^n, t \in \mho^t \quad (3)$$

- Constraints

$$D^{newmetro}_{n,t} = D^{metro}_{n,t} - P^{MG2M}_{n,t} - P^{V2M,dch}_{v,r,n,t} \quad \forall n \in \mho^n, r \in \mho^r, \forall v \in \mho^v, \forall t \in \mho^t \quad (4)$$

$$P^{M2MG}_{n,t} \leq P^{rb}_{n,t} \quad \forall n \in \mho^n, t \in \mho^t \quad (5)$$

2.2 | The definition of M2V

As stated, the energy exchange between MS and EVs is performed via M2V technology. In this regard, Equation (6) shows the total profit of M2V considering the fact that charging and discharging of EVs are taken into account as the financial outcome and income of MS, respectively. Equations (7) and (8) confine the amount of energy exchanged.

- Objective functions

$$Profit_{M2V} = \sum_{n \in \mho^n, r \in \mho^r} B2^n_i \times \left(P^{V2M,ch}_{v,r,n,t} - P^{V2M,dch}_{v,r,n,t} \right) \quad \forall n \in \mho^n, r \in \mho^r, \forall v \in \mho^v, \forall t \in \mho^t \quad (6)$$

- Constraints

$$P^{V2M,ch}_{v,r,n,t} \leq P^{rb}_{n,t} \quad (7)$$

$$D^{newmetro}_{j,t} = D^{metro}_{j,t} - \sum_{n \in \mho^n, f \in \mho^{fl}} B2^n_i \times \left(P^{V2M,ch}_{v,r,n,t} - P^{V2M,dch}_{v,r,n,t} \right) \quad \forall n \in \mho^n, r \in \mho^r, \forall v \in \mho^v, \forall t \in \mho^t \quad (8)$$

2.3 | The definition of V2M and V2MG

Through V2X technologies, EVs can make a huge profit by energy exchange. This can be found in Equation (9) where the profit of EVs comprise the earnings from V2M and V2MG (Equations (10), (11)), however, the degradation cost of batteries should be considered as Equation (12). Equations (13)–(21) represent the different constraints that limit the energy exchanges of EVs.

- Objective functions

$$Profit_V = Profit_{V2MG} + Profit_{V2M} - \sum_{v \in \mho^v} Cost^{deg}_f \quad (9)$$

$$Profit_{V2MG} = \sum_{t \in \mho^t, v \in \mho^v} \left(B1_{v,t} \times P^{V2MG}_{v,t} \right) \quad (10)$$

$$Profit_{V2MG} = \sum_{t \in \mho^t, v \in \mho^v} \left(B2_{v,t} \times P^{V2M}_{v,t} \right) \quad (11)$$

$$Cost^{deg}_v = B^v_{deg} \times \sum_{n \in \mho^n, r \in \mho^r, t \in \mho^t} b\left(P^{V2MG,dch}_{v,r,t} + P^{V2M,dch}_{v,r,n,t} \right) \quad \forall v \in \mho^v \quad (12)$$

- Constraints

$$E1^{v2mg}_t = E1^{v2mg}_{t-1} + P^{V2MG,ch}_{v,r,t} \times \eta^{ch}_{es} - P^{V2MG,dch}_{v,r,t} \times \eta^{dch}_{es} \quad \forall r \in \mho^r, \forall v \in \mho^v, \forall t \in \mho^t \quad (13)$$

$$E2^{v2m}_t = E2^{v2m}_{t-1} + \sum_{n \in \mho^n, r \in \mho^r} (P^{V2M,ch}_{v,r,n,t} \times \eta^{ch}_{es} - P^{V2M,dch}_{v,r,n,t} \times \eta^{dch}_{es}) - \sum_{v \in \mho^v, r \in \mho^r} b^r{}_{v,r,n,t} \times (RL^{ev}_{v,r} - RC^{ev}_{v,r}), \quad \forall v \in \mho^v, r \in \mho^r, \forall n \in \mho^n, \forall t \in \mho^t \quad (14)$$

$$E^{ev}_{total} = E1^{v2mg}_{v,t} + E2^{v2m}_{v,t} \quad \forall v \in \mho^v, t \in \mho^t \quad (15)$$

$$P^{V2MG}_{v,t} = E1^{v2mg}_{v,t} + E1^{v2mg}_{v,t-1} \quad \forall v \in \mho^v, t \in \mho^t \quad (16)$$

$$P^{V2M}_{v,t} = E1^{v2m}_{v,t} + E1^{v2m}_{v,t-1} \quad \forall v \in \mho^v, t \in \mho^t \quad (17)$$

$$b^{ev,ch}_{v,r,n,t} + b^{ev,dch}_{v,r,n,t} = bb^{ev}_{v,r,n,t} \quad \forall v \in \mho^v, t \in \mho^t \quad (18)$$

$$b^{ev,ch}_{v,r,n,t} R^{ev,ch}_{\min} \leq R^{ev,ch}_{v,r,n,t} \leq b^{ev,ch}_{v,r,n,t} R^{ev,ch}_{\max} \quad \forall n \in \mho^n, r \in \mho^r, \forall v \in \mho^v, \forall t \in \mho^t \quad (19)$$

$$b^{ev,dch}_{v,r,n,t} R^{ev,dch}_{\min} \leq R^{ev,dch}_{v,r,n,t} \leq b^{ev,dch}_{v,r,n,t} R^{ev,dch}_{\max} \quad \forall n \in \mho^n, r \in \mho^r, \forall v \in \mho^v, \forall t \in \mho^t \quad (20)$$

$$C^{ev}_{\min,v} \leq E^{ev}_{total,v} \leq C^{ev}_{\max,v} \quad \forall v \in \mho^v, t \in \mho^t \quad (21)$$

2.4 | The water unit model

To model the water demand it is necessary to define the structure of water demand supplement. The proposed model considers the desalination unit as well as primary/secondary tanks. Having been desalinated, the water is transferred to the primary tank. The secondary tank, which is connected bilaterally to the primary one and the water grid as well, enjoys two sets of input and output. The water stored in the secondary tank is injected to the hub through one of these outputs. Figure 2 schematically illustrates this system. Equations (22)–(28) provide the formulation that govern the desalination unit of SEHs.

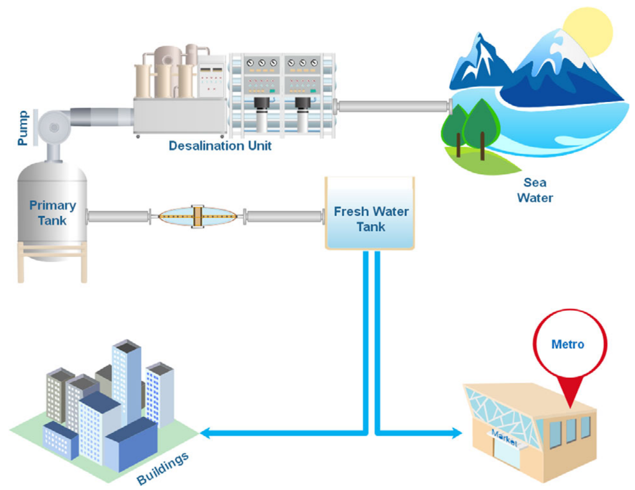

FIGURE 2 The water demand supplement system of smart island

- The operational constraint of Primary tank

$$V_{\max,t}^{dt} = V_{\max,t-1}^{dt} + W_t^{d,in} - W_t^{d,out} \qquad t \in \mho^T \tag{22}$$

- The operational constraint of secondary tank

$$V_t^{st} = V_{t-1}^{st} + W_t^{d,out} - W_t^{s,out} \qquad t \in \mho^T \tag{23}$$

- The capacity limitation of Primary tank

$$0 \le V_t^{DT} \le V_{\max,t}^{dt} \qquad t \in \mho^T \tag{24}$$

- The capacity limitation of secondary tank

$$V_{\min}^{st} \le V_t^{st} \le V_{\max}^{st} \qquad t \in \mho^T \tag{25}$$

- Input bounds of the unit

$$W_{\min}^{d,in}.I_t^d \le W_t^{d,in} \le W_{\max}^{d,in}.I_t^d \qquad t \in \mho^T \tag{26}$$

- Output bounds of the unit

$$0 \le W_t^{d,out} \le W_{\max}^{d,out} \qquad t \in \mho^T \tag{27}$$

- Consumed power of the unit

$$P_t^{wdu} = W_t^{d,in}.CF^{wdu} \qquad t \in \mho^T \tag{28}$$

2.5 | Microgrid objective function

Here, the objective function aims to minimize the total cost of the smart island. All in all, the profits of M2MG, M2V and V2X form the total profit of the island that should be subtracted from total cost according to Equation (29). Equation (30) demonstrates the balance between the output and input power of MG that should be asserted to be true for all given time slots upon each component.

- Objective function

$$cost_{Total} = cost_{Metro} - (Profit_{EV} + Profit_{M2MG} + Profit_{M2V}) \tag{29}$$

- Constraints

$$P_{exchange}^{MG} = Load^{MG} - \sum_{n\in\mho^n, v\in\mho^v, t\in\mho^t} P_{n,t}^{M2MG} + P_{v,t}^{V2MG} - P_t^{seb} + P_{n,t}^{MG2V} \tag{30}$$

2.6 | The constraints of SEH

The boundaries of active power input into SEH at time t is determined by Equation (31). Equation (32) prevents the processing electric power to be violated from the nominal capacity, while Equation (33) represents the capacity of storages within SEH. The limits for charging and discharging power rates are guaranteed by Equations (34) and (35). Equation (36) controls the state of charging or discharging. The balance of SEH in terms of heat and electricity is attained by applying Equations (37) and (38). When it comes to the balance between gas and power, Equation (39) adjusts the input to SEH. Last but not least, Equations (40)–(42) represent the restrictions of energy transformation within SEH.

$$P_{\min,t}^{seb} \le P_t^{seb} \le P_{\max,t}^{seb} \quad ,\forall t \in \mho^t \tag{31}$$

$$L_{\min}^{es} \le L_t^{es} \le L_{\max}^{es} \quad ,\forall t \in \mho^t \tag{32}$$

$$L_t^{es} = \left(1 - \eta_{es}^{loss}\right) L_{t-1}^{es} + P_t^{es,ch} - P_t^{es,dch} \quad ,\forall t \in \mho^t \tag{33}$$

$$\frac{1}{\eta_e^{ch}} R_{\min}^{es} b_t^{seb,ch} \le P_t^{ch} \le \frac{1}{\eta_e^{ch}} R_{\max}^{es} b_t^{seb,ch} \quad ,\forall t \in \mho^t \tag{34}$$

$$\eta_e^{dch} R_{\min}^{es} b_t^{seb,dch} \le P_t^{dch} \le \eta_e^{dch} R_{\max}^{es} b_t^{seb,dch} \quad ,\forall t \in \mho^t \tag{35}$$

$$0 \le b_t^{seb,ch} + b_t^{seb,dch} \le 1 \quad ,\forall t \in \mho^t \tag{36}$$

$$P_t^{seb,e} + P_t^{wdu} = \eta_e^T . P_t^{seb} + \eta_{chp}^{G/E} . G_t^{chp,in} + P_t^{es,dch} - P_t^{es,ch} , \forall t \in \mho^t \tag{37}$$

$$P_t^{seb,h} = \eta_{chp}^{G/H} . G_t^{chp,in} + \eta_{boi}^{G/H} . G_t^{chp,in} \quad ,\forall t \in \mho^t \tag{38}$$

$$G_t^{seb,in} = G_t^{boiler,in} + G_t^{chp,in} \quad ,\forall t \in \mho^t \tag{39}$$

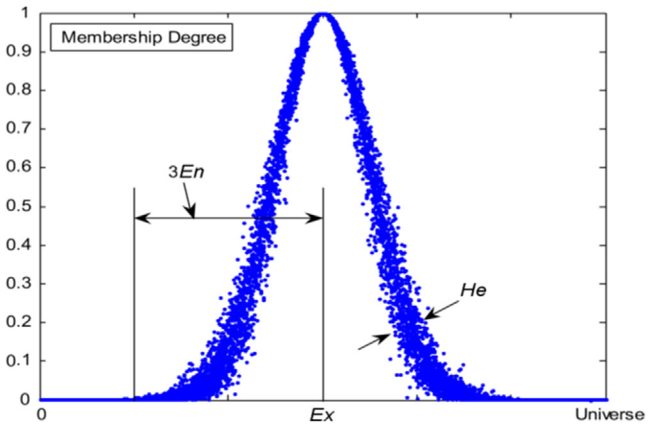

FIGURE 3 Cloud model for normal distribution [38]

$$\eta_e^T P_t^{seb} \le C^T \qquad , \forall t \in \mho^t \tag{40}$$

$$\eta_{chp}^{G/H} \cdot G_t^{chp,in} \le C^{CHP} \qquad , \forall t \in \mho^t \tag{41}$$

$$\eta_{boiler}^{G/H} \cdot G_t^{boiler,in} \le C^{B} \qquad , \forall t \in \mho^t \tag{42}$$

3 | CLOUD THEORY BASED STOCHASTIC FRAMEWORK

In this paper, cloud theory (CT) is adopted to effectively capture the uncertainty associated with some parameters in the problem. Generally speaking, the aim of CT is to convert qualitative parameters into quantitative ones representing uncertainties mathematically. It is worth noting that this concept is carried out based on fuzzy theory. Equation (43) shows the basic concept of CT.

$$C_L(k) : m \to [0,1], \forall k \in m, k \to C_L(k) \tag{43}$$

Where L appears to be the language value of domain m, and C_L stands for the mapping process or cloud. Here the model is known as the normal cloud model, as the cloud obeys normal distribution. There are three main characteristics to specify the cloud ($C_L(k)$) as shown in Figure 3:

a. Expectation (Ex): This variable specifies the mean value of the cloud, which is easily computed in realistic problems.
b. Entropy (En): This variable not only limits the fluctuation of the cloud and determines the bandwidth, but also shows the degree of variable's fuzziness.
c. Hyper Entropy (HEn): This variable specifies the dispersion and diversity of the cloud's drops. More specifically, HEn can be referred to as the entropy of the En which is the entropy itself. This feature makes CT superior to other similar methods including Monte Carlo simulation (MCS) in capturing the uncertainties. Figure 4 demonstrates the idea of HEn.

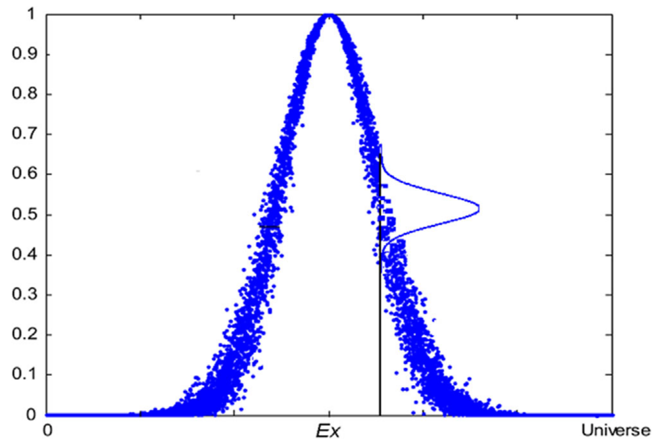

FIGURE 4 The idea of HEn for normal distribution [38]

Having been determined, Ex, En and HEn constitute the model of the cloud drop (k_i, m_i). Here, k_i is the random variable, while m_i can be described as the membership degree. The latter also represents the probability of drops in the cloud membership. Following steps show how cloud drops are generated:

Step I: Generate a normal random value (En'_i), while En and HEn are the expected value and hyper entropy, respectively.

Step II: Generate a normal random value (k_i), while Ex and En'_i are the expected value and hyper entropy, respectively.

Step III: Using the Equation (44), compute the value of m_i to obtain a drop model:

$$m_i = e^{-\frac{(k_i - Ex)^2}{2(En'_i)^2}} \tag{44}$$

Step IV: Repeat the three previous steps until D drops are generated. Then, since this method utilizes forward-backward approach to produce the cloud, above process should be adopted inversely in order to do mapping between the qualitative and quantitative data.

Step V: After completion the process of drops generation ((k_i, m_i); $i = 1, 2, \ldots, D$), the three discrete characteristics are obtained by the following calculation:

$$Ex = \frac{1}{D}\sum_{i=1}^{D} k_i \tag{45}$$

$$En_i = \sqrt{\frac{(k_i - Ex)}{-2\ln(m_i)}} \tag{46}$$

$$En = \frac{1}{D}\sum_{i=1}^{D} En_i \tag{47}$$

$$He = \sqrt{\frac{1}{D}\sum_{i=1}^{D} (En_i - En)^2} \tag{48}$$

4 | PROBLEM SOLVING METHOD

Behaviours in nature have always inspired engineering and mathematical methods. Among the methods developed based on swarm intelligence, the intelligent water drops (IWDs) algorithm is based on the dynamic of river systems and the cooperation of these drops. This algorithm is designed to model actions within a river and turns and twists. Two important features of IWD are soil and velocity, which are known as variables in the period of IWD. At the beginning of the movement and the path, the values of both are specified, which means the former is equal to zero and the latter has an specific initial value. Depending on the amount of soil, the IWD speed can vary. Obviously, the higher the amount of soil between the two points is, the lower the speed would be. In fact, velocity has an inversely proportional non-linear relationship with the soil. The time required for this distance can be calculated through the linear motion equation. Therefore, the travel time between two points is inversely related to the distance between the two points and is directly related to velocity. Also, because there is less soil in areas where more IWDs are available, it can be said that soil is a source of information that remains in the memory of the environment and water drops [38], [39].

With this in mind, the IWD must identify its next step in the new situation by a mechanism. Given the above description, routes with less soil will have a better chance of being traversed by the IWD. The IWD algorithm uses graph representation to solve the problem. The set of vertices and edges are shown as *(N, E)*. Therefore, each IWD finds the appropriate solution by passing the vertices through the edges. When all IWDs find their solution, an iteration of the problem ends. By finding the optimal one among the solutions obtained in an iteration, the globally-optimal solution is found. Considering the best solution, the amount of soil in the route decreases based on its quality. Subsequent iterations are also performed with new IWDs. The algorithm stops performing when it reaches the maximum number of iterations or the optimal global solution with a desired quality. It should be noted that this method is able to find the optimal solution when sufficient number of iterations is performed [38]. In this algorithm, two types of parameters, static and dynamic, are considered. Static parameters are constant throughout the solving steps, while dynamic parameters are reinitialized in each iteration. Based on Figure 5, the

FIGURE 5 General steps of IWD algorithm

TABLE 1 Constant parameters in IWD algorithm

Notation	Value	Parameter (s)
a_v, b_v, c_v	1, 0.01,1	Velocity updating
a_s, b_s, c_s	1, 0.01,1	Soil updating
μ_m	0.9	Local soil updating
μ_{IWD}	0.9	Global soil updating
soil (i, j)	*InitSoil* (User selected) = 10000	Initial soil on each edge
VL_{int} *(IWD)*	*InitVel* (User selected) = 200	Initial velocity of each IWD

IWD algorithm finds the globally-optimal solution in four general iterative steps.

Step I: This step is devoted to graph representation and the specification of the static and dynamic parameters of the algorithm. Static parameters include the initial quality of the optimal solution which is equal to negative infinity ($-\infty$) in the initial conditions, the maximum number of iterations, and the number of IWDs, which is usually equal to the number of vertices. In addition, Table 1 shows the other constant parameters in this algorithm. Now, the dynamic parameters including the list of vertices traversed by each IWD (TV(IWD)), should be set. It should be stated that none of the IWDs initially have soil. IWDs must be distributed haphazardly on graph vertices before the next step get performed. At this point, the first vertex traversed by each IWD is determined. In the next steps, the list of visited points will be updated.

Step II: The goal of this step is to find the local solutions for IWDs:

- Firstly, find the next vertex for an IWD so that the constraints of the problem are not violated. Also, the destination node should not be previously listed as traversed by that IWD. The probability of selecting the targeted node is calculated by Equation (49). The newly passed vertices are added to the TV(IWD) list.

$$P_j^{IWD}(j) = \frac{f\left(soil(i,j)\right)}{\sum_{k \notin TV(IWD)} f\left(soil(i,k)\right)} \tag{49}$$

Such that:

$$f(soil(i,j)) = \frac{1}{\varepsilon_s + g\left(soil(i,j)\right)} \tag{50}$$

And:

$$g(soil(i,j)) = \begin{cases} soil(i,j) \quad if \quad \min\limits_{l \notin TV(IWD)} (soil(i,l)) \geq 0 \\ soil(i,j) - \min\limits_{l \notin TV(IWD)} (soil(i,l)) \quad else \end{cases} \tag{51}$$

- The velocity of IWDs moving from i toward j is updated by below equation. Thus, $VL_{t+1}(IWD)$ denotes the next value for this parameter.

$$VL_{t+1}(IWD) = VL_t(IWD) + \frac{a_v}{b_v + c_v.\, soil^2(i,j)} \tag{52}$$

- Using the following equations, the amount of soil loaded by IWD ($\Delta soil\ (i,j)$) is calculated. In these equations the heuristic undesirability $HUD(j)$ is determined according to the problem.

$$\Delta soil(i,j) = \frac{a_s}{b_s + c_s.time^2\left(i,j; VL_{t+1}(IWD)\right)} \tag{53}$$

Such that:

$$time\left(i,j; VL_{t+1}(IWD)\right) = \frac{HUD(j)}{VL_{t+1}(IWD)} \tag{54}$$

- The updated soil of the routs, and the amount of soil loaded by IWDs are calculated by Equation (55).

$$\begin{aligned} soil(i,j) &= (1-\rho_n).soil(i,j) - \mu_m.\Delta soil(i,j) \\ soil^{IWD} &= soil^{IWD} + \Delta soil(i,j) \end{aligned} \tag{55}$$

Step III: This step aims to find the best solution for IWDs, which includes several stages:

- Firstly, the globally optimal solution of the current iteration, denoted by S_{It}, is calculated based on all obtained solutions in a given iteration. It should be noted that the function f represents the quality of the solutions.

$$S_{It} = \arg \max_{\forall S^{IWD}} f(S^{IWD}) \tag{56}$$

- Next, update the soil in the routs that make up the S_{It} in this iteration. The number of vertices passed in this solution is represented by N_S.

$$\begin{aligned} soil(i,j) &= (1+\mu_{IWD})\, .\, soil(i,j) \\ &-\mu_{IWD} \cdot \frac{1}{(N_S-1)} \, .\, soil_{It}^{IWD} \quad \forall (i,j) \in S^{It} \end{aligned} \tag{57}$$

- Now the total optimal solution GS can be obtained through comparing the best solution of each iteration as the following equation:

$$GS = \begin{cases} S_{It} & if\ \ q(S_{It}) \geq q(GS) \\ GS & otherwise \end{cases} \tag{58}$$

Step IV: After performing the previous steps, if the iteration number does not still reach It_{max}, go to the next iteration and perform the calculations from the beginning, step I. It is also worth recalling that the static parameters are constant throughout the whole procedure, while the dynamic parameters need to be recalculated.

5 | NUMERICAL CASE STUDY

In this section the proposed model of the smart island is evaluated. As mentioned above, the model comprises SEH, MGs with different RESs (wind, solar and tidal units), and STS. Moreover, the elements within STS such as EV parking lots and MS are able to exchange energy with each other through dispersed stations that should be optimally allocated. To this end, six locations are candidated for the establishment of three parking lots. Table 2 gives the specifications of the EV fleets in detail [1, 40]. To evaluate the performance of each part of the smart island model, three distinct cases are briefly analyzed in the following. The cases include the energy exchange of STS, MG and SEH. Additionally, the uncertainty effects imposed to SEH is considered as a separate case study.

As mentioned before, SEH has its own energy transactions with other components. Figure 6 gives the amount of water demands of MS stations supplied by SEH in a 24-h period of time. It is worth mentioning that a CHP unit provides the

TABLE 2 The EVs fleets specifications

Fleet	Number of EVs	Access time	Capacity (kWh)		Charge/discharge rate (kW)	
			Min	Max	Min	Max
1	40	7–8, 12–13, 15–17	219	1644	7.3	292
2	63	7–10, 12–14, 17–19	263	1973	7.3	496
3	54	7–10, 12–14, 17–19	251	1902	7.3	386
4	33	12–14, 16–18	208	1610	7.3	234
5	54	7–10, 12–14, 17–19	251	1902	7.3	386
6	39	7–9, 12–14, 16–18	219	1644	7.3	292

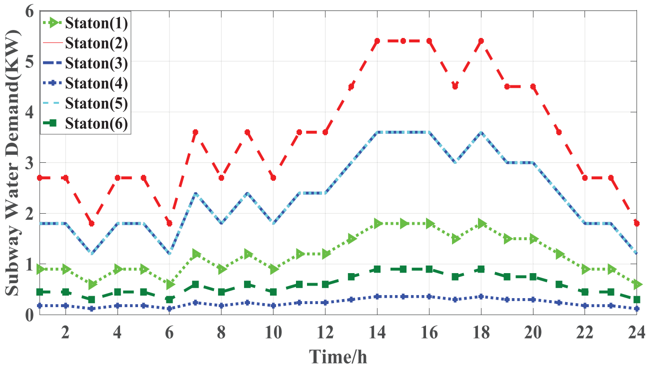

FIGURE 6 The amount of water demanded by metro stations

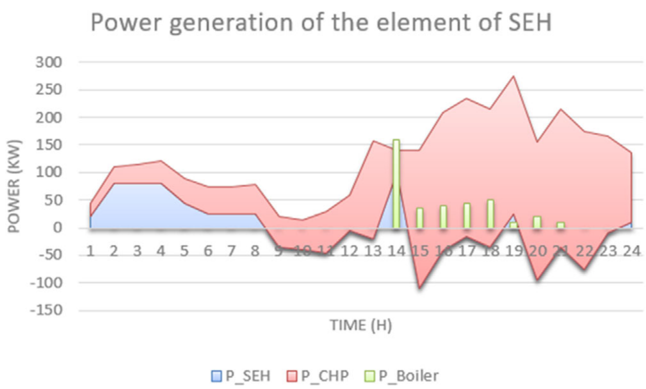

FIGURE 7 Power generation of the elements of SEH

electricity demands of these stations. With this in mind, during the hours that the generation exceeds the energy demand, SEH is able to sell its additional energy to MG. Conversely, SEH purchases the required energy from MG in some hours. The CHP and boiler energy generation, along with the energy exchange of SEH is depicted in Figure 7. Obviously, the positive and negative values imply MG-to-SEH and SEH-to-MG direction of energy exchanges, respectively. From SEH point of view, purchasing electricity from MG is more affordable in some periods, meaning that SEH supplies its own demands from MG rather than CHP. However, when the expense of generating electricity by CHP is lower than that of buying from MG, SEH would rather supplying the demands from MG, and even sell the excess amount of generated energy to make profit. As seen in Figure 7 this is the case in the period between hours 15 and 24.

Different components of the smart island are subject to uncertainties. The proposed model tries to address the uncertainty associated with EVs' arrival time to the stations that depends on the traffic jam. Additionally, the intermittent output of wind and solar generations and the varying demand of SEH for heat and power are considered. This subsection aims to examine the impact of aforementioned sources of uncertainty on the smart island. As stated in the previous sections, the cloud theory (CT) as an effective method, is employed to capture these uncertainties in the model. Since the components of the smart island are interdependent, the variations within each component may influence the rest of the island. The comparison between

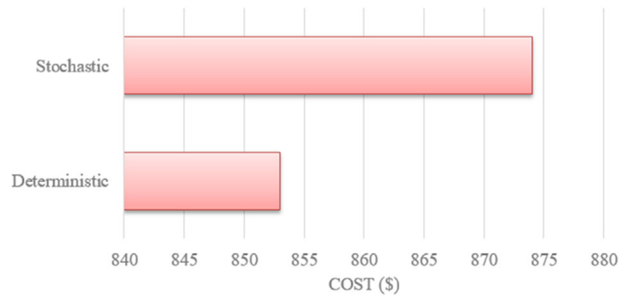

FIGURE 8 SEH's cost in deterministic and stochastic conditions

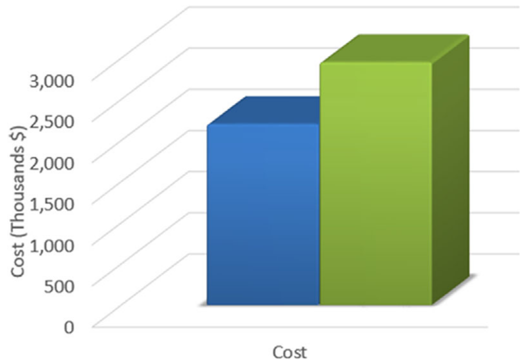

FIGURE 9 Metro's cost in deterministic and stochastic conditions

the costs of SEH in two conditions, stochastic and deterministic, are made in Figure 8. It is observed that the cost of SEH in the stochastic model is about 1.6% more than deterministic condition. Also, Figure 9 compares these costs for MS and shows that there is an over 31% increase when the system is analyzed in the stochastic manner. The considerable rise in MS cost is mainly due to the numerous interactions that this system has with other components whether within STS or not. This asserts that uncertainties are more likely to impact MS.

6 | CONCLUSION

The main purpose of this paper is to model a smart island containing several components such as smart energy hub (SEH), microgrid (MG), and smart transportation system (STS). Based on the model, these components interactively exchange multi-carrier energy including power, heat, gas and water. To provide an example, the total cost of the metro system (MS) lessens by providing the required water from SEH. Furthermore, the optimal allocation of exchange points within MS is addressed in this paper which significantly decreases the total cost. In addition, since the uncertainties associated with different components markedly impact the performance of the island, the authors have reported the analysis of uncertain conditions. It can be seen that in the proposed model, STS is more susceptible to uncertainties because of the unpredictable road traffic and the varying outputs of the renewable energy sources (RESs) within MG. Accordingly, future works and researches can be devoted to improving the accuracy of uncertainty quantification.

It is worth bearing in mind that the future grids would embrace various sources of energy and they are likely not to be limited to those mentioned here. Therefore, in addition to developing more precise models for handling uncertainties, there is a need to develop a model considering different sources and carriers such as gas captured from electrolysers or chemical reactions. The role of storages and their impacts on system operation is also worth considering.

NOMENCLATURE

Sets/Indices

J^V/v Set/index of EV fleets. $J^v = \{1,\ldots,6\}$.

J^r/r Set/index of city routes. $J^r = \{1,\ldots, 12\}$.

J^t/t Set/index of time. $J^t = \{1,\ldots,24\}$.

J^n/n Set/index of metro stations. $J^n = \{1, \ldots,6\}$.

Constants

$B^v_{\deg}$ The degradation cost of EV fleet batteries.

$E^{ev}_{s,r}$ EV energy consumption while being driven towards station s via the route r.

$R^{es}_{\max}, R^{es}_{\min}$ Maximum and minimum rate of storage batteries charging.

$L^{es}_{\max}, L^{es}_{\min}$ Maximum and minimum level of storage batteries charger.

$P^{seh}_{\max}, P^{seh}_{\min}$ Maximum and minimum input or output power of smart energy hub

a_v, b_v, c_v The updating coefficients of velocity in IWD algorithm.

a_s, b_s, c_s The updating coefficients of soil in IWD algorithm.

μ_m, μ_{IWD} The updating coefficients of local and global soil in IWD algorithm.

$C^{ev}_{\max}, C^{ev}_{\min}$ Maximum and minimum capacity of the EV fleet batteries.

$R^{ev,ch}_{\max}, R^{ev,ch}_{\min}$ Maximum and minimum charging rate of EV fleet batteries.

$R^{ev,dch}_{\max}, R^{ev,dch}_{\min}$ Maximum and minimum discharging rate of EV fleet batteries.

$P^{seh,e}_t, P^{seh,h}_t$ Smart energy hub demands (Electricity and heat) in time slot t.

$B1^n_v, B2^n_v, B2^n_i$ V2MG, V2M, and M2V/M2MG energy exchange bidding prices

$C^{CHP}/C^B/C^T$ Nominal capacity of the CHP/boiler/transformer.

D The number of drops in the cloud theory.

It_{max} The maximum number of iterations in IWD algorithm.

Variables

$b^r_{v,r,n,t}$ Binary variable related to the city routes

E^{ev}_{total} The total energy exchanges of EV fleets

$RL^{ev}_{v,r}$ The amount of EV charging of by the recharging lines

$RC^{ev}_{v,r}$ The EV electricity consumption in the traffic of residential roads

$P^{rb}_{n,t}$ Maximum amount of regenerative braking energy (RBE).

P^{seh}_t The energy exchange between SEH and the grid in time slot t.

$G^{seh,in}_t$ The input gas power of SEH in time slot t.

$G^{boiler,in}_t, G^{chp,in}_t$ The input gas power of CHP and boiler in time slot t.

S^{es}_t The remaining energy of storages in SEH in time slot t.

$V^{dt}_{\max,t}$ Maximum volume of desalination tank.

V^{st}_t Secondary tank water volume during time slot t.

V^{dt}_t Desalination unit water volume in time slot t.

$W^{d,out}_t$ Desalination unit output water in time slot t.

$W^{s,out}_t$ The output of secondary tank in time slot t.

$W^{d,in}_t$ The input of desalination unit in time slot t.

$W^{d,out}_{\max}$ Maximum output water of desalination unit.

P^{wdu}_t Consumed power of the water desalination unit

LS^{IWD} The amount of soil loaded by each IWD.

S_{It}, GS The optimal solution of each iteration, and the total optimal solution

$E1^{v2mg}, E2^{v2m}$ The capacity of EV fleet batteries during V2MG, V2M

$b^{seh,ch}_t, b^{seh,dch}_t$ The binary variables of charging and discharging modes of smart energy hub storages.

$P^{seh,e}_t, P^{seh,h}_t$ Smart energy hub demands (Electricity and heat) in time slot t.

$D^{newmetro}_{j,t}, D^{metro}_{j,t}$ Metro demand after/before making changes in the base profile.

$P^{V2MG}_{v,t}, P^{V2M}_{v,t}$ V2MG, and V2M, energy exchange.

$P^{M2MG}_{n,t}, P^{MG2M}_{n,t}$ Energy exchanges between metro and microgrid.

$P^{V2M,ch}_{v,r,n,t}, P^{V2M,dch}_{v,r,n,t}$ Charging and discharging power while V2M exchanging.

$R^{ev,ch}_{v,r,n,t}, R^{ev,dch}_{v,r,n,t}$	Charging and discharging rates of vehicle v on the route r, at station *n*, at time *t*, respectively.
$V^{st}_{\max}, V^{st}_{\min}$	Maximum and minimum volume of desalination secondary tank.
$W^{d,in}_{\max}, W^{d,in}_{\min}$	Maximum and minimum input water of desalination tank.
$P^{V2MG,ch}_{v,r,t}, P^{V2MG,dch}_{v,r,t}$	Charging and discharging power while V2MG exchanging.
$b^{ev,ch}_{v,r,n,t}, b^{ev,dch}_{v,r,n,t}, bb^{ev}_{v,r,n,t}$	Binary variables related to the charging, discharging of the EVs.
$\Pr ofit_M, \Pr ofit_V, \Pr ofit_{V2MG}, \Pr ofit_{M2V}, \Pr ofit_{M2MG}$	The profits of metro, EV fleet, V2MG, M2V, M2MG, and M2V, respectively.
$\eta^{loss}_{es}, \eta^{ch}_{es}, \eta^{dch}_{es}$	The loss efficiency of SEH storages, and charging/discharging efficiencies.
$\eta^{T}_{e}, \eta^{ch}_{e}, \eta^{dch}_{e}, \eta^{G/H}_{boiler}, \eta^{G/H}_{chp}, \eta^{G/E}_{chp}$	Transformer and charging/discharging efficiency, and energy conversion efficiency of: Gas/heat conversion of the boiler; Gas/heat conversion of the CHP; Gas/electricity conversion of the CHP.
$cost^{v}_{\deg}, \cos t_{M2MG}, cost_{sbt}, cost_{Metro}$	The costs of EV batteries degradation, M2MG, storage batteries and metro demand supply, respectively.
$P^{es,ch}_{t} / P^{es,dch}_{t}$	Charging/discharging power of the storage batteries in time slot *t*.
k_i	Random value related to the cloud theory
m_i	The membership degree related to the cloud theory
N_S	The number of nodes in the solution S_{It}
P^{IWD}	The probability of the next move of each IWD
soil (i, j)	The amount of soil on each edge in IWD algorithm.
TV(IWD)	The list of vertices traversed by each IWD
VL(IWD)	The velocity of each IWD.

FUNDING INFORMATION

None.

CONFLICT OF INTEREST

There is no conflict of interests.

DATA AVAILABILITY STATEMENT

Data would be available as per request from the authors.

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How to cite this article: Esapour, K., Moazzen, F., Karimi, M., Dabbaghjamanesh, M., Kavousi-Fard, A.: A Novel energy management framework incorporating Multi-Carrier Energy Hub for smart city. IET Gener. Transm. Distrib. 17, 655–666 (2023). https://doi.org/10.1049/gtd2.12500