Towards a Coefficient Secure IoT Energy Framework within the Smart City: Advanced Encryption Standard

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Abstract—**The concept of a smart city is intertwined with a kind of great data management, and through which, reaching optimal management. The data transaction and the issue of communication between different equipment are all defined on the IOT platform. The concept of IOT is a general keyword referring to the widespread communication between equipment. Nevertheless, the idea that metropolitan management can be implemented with the targeted data processing faces challenges. On the other hand, multicarrier energy management, in which various types of energy generating structures like microgrids, smart grid, energy hub systems, transportation sector, etc. converge together in an optimal energy management program, is of great difficulty. Considering these challenges, the processes of encryption, dispatching data, decryption with the algorithm of the energy management plan should be intertwined and all solved together as a general problem. The current paper has presented a modified IOT architecture along with a multi-carrier energy management application through integrating two distributed and integrated management approaches. In the presented model, each energy-generating agent in the first layer initially controls its own internal supply and demand rate implementing distributed management, and then in the second layer, each agent participates in a macro-competitive market to achieve the optimal work point. Thus, in the presented model, the data blockchain building protocol based on The Advanced Encryption Standard (AES) in IOT platform is synchronized with the cloud-computing center and an integrated energy and data security management program is run, having the nature of the competitive market according to the block building time by each agent. According to the results, in this approach, while achieving the desired answer, the volume of data transaction and consequently, the time to gain the final consensus may be considerably reduced.**

Index Terms—**Smart city, energy transaction, data security, AES, IoT, cyber-attacks.**

I. Introduction

A. Motivation and Aims

With today's lifestyle in metropolises, the city's management is veritably tussling with complicated recent challenges involving a lot of different parts such as greenhouse gas emission, economic development, conservation of natural sources, traffic and its energy consumption affair, etc. [1]. It seems that the chief mentioned challenges can clear up through communication among urban utilities like power systems, water, wastewater, and transportation by expanding the implementation of smart city's essentials [2]. The foundation of the smart city has gotten established based on interconnectivity among all agents in a way that data security and safe communication are two pillars of it [3]. On the other hand, the energy production description is right on the nose in the smart city's concept, which involves various types. In this infrastructure, distributed energy resources (DERs), energy hub systems, renewable energies, power grids, and microgrids can adequately perform well role. All classifications have been surveyed by researchers in [4] and [5] references.

B. Literature Review

One of the major targets of the implementation of the smart city's idea is production and consumption management in a dynamic manner in which the consumers must have an active presence. Hence, the management of the smart city fails if it does not fulfill the prerequisite of active consumer participation. The establishment of the required infrastructure is verily a significant challenge for the management of the demand side. Of course, there are several similar challenges also on the production side [6]. Meanwhile, energy control in urban traffic management and smart homes are the two main effective agents contributing to manage consumption on the demand side. The complexity of implementing demand side energy management is since it depends on the social behavior of citizens for the maximum acceptance of protocols, besides its need of creating hardware infrastructure. This issue will become even more difficult in case of considering the problem of uncertainty in renewable energy sources.

C. Smart city

The idea of a smart city was formed in order for creating synergy between production and consumption as much as possible. Hence, modeling a smart city includes different parts, whose main components include the smart grids, microgrids, transportation, and hub systems. In the following, the recent papers on the impact of each section will be reviewed.

1) Smart Grid

Recent advances in building communication technologies have also infiltrated into the power industry infrastructures. The infiltration of these devices has realized the smart power grid control. In the beginning, this led to a more favorable exploitation of the wide power grid and significantly increased the reliability index of the grid [6]. After this successful test caused by the infiltration of communication technologies as well as its integration with power grid control equipment like circuit breakers, to enhance efficiency, the issue of connecting the power grid to an urban system's other service sectors and planning for that has become a topic of interest for researchers in the recent few years.

2) *Transportation Systems*

Nowadays, the electric vehicles' rapid growth has been very considerable and impressive. In this regard, their peripheral technologies are being upgraded, too, so that two-way energy exchange between vehicle charging stations and the grid (vehicle to grid/V2G technology) has become possible. The researchers in reference [7] have considered the two-way energy exchange system's performance between the transportation sector and the power grid as a random V2G model given its random nature. Reference [8] has examined the V2G system's performance considering its uncertainty in the presence of renewable generation sources. On the other hand, the transportation sector does not merely include cars, but the urban train sector has to be definitely considered. Urban trains may also inject power into the grid when necessary. This power can be injected through regeneration and braking energy storage, comprehensively researched in references [9 &10]. Reference [11] has described how to obtain energy from an urban train's braking system.

3) *Energy Hub & Synergy mechanism*

As mentioned, in the optimal management of the smart city, the synergy between various energy sectors is of significant effect. On the other hand, various types of energy may be converted into each other. This idea is implemented in a complex called energy hub system, optimally controlling industrial, residential, and commercial energy consumption in water, electricity, and gas sectors. Reference [12] has investigated planning for different types of energy demand under the function of these energy supply systems. Reference [13] has revealed the presence of these multi-purpose systems and its effect on the smart city management performance. In [14], the authors have sought to present an energy management program aiming at minimizing the EH systems' operating cost in the smart energy grid. On the other hand, as previously mentioned, in a smart city, the management of the energy sector on the demand side is so dynamic, and reference [15] focuses on the operation performance of residential EHs. The synergy system between multicarrier structures is another issue, whose integration with the presence of renewable energy sources as well as the transportation sector references have been examined in [16-18]. Nevertheless, the issue is not limited to hardware and operation aspects, and for stable operation, the data exchange security in multicarrier structures has to be maintained.

4) *IoT & Security Framework*

Communication, data collection and processing, and decision-making according to the correct processing of data are indispensable factors for optimal management of smart cities. Development of the Internet of Things' (IoT) infrastructure has provided the ground for partial realization of the above three factors by operationalizing communication of the components of a smart city and exchange of data between them. On the other hand, in such a structure, it is very important to maintain the authenticity, confidentiality and integrity of the data in all stages up to the point the final decision is reached and a command is forwarded to the agents. However, ensuring data security without disrupting the communication between the components has come to be known as a major challenge. In the present study AES algorithm was used to maintain data security and configure the length of data required for communication between agents until the final decision is reached. For doing so, a protocol is used for exchange of data between independent agents. A review of recent literature adopting this algorithm to maintain data security and reflecting its true potential can truly show why the author has chosen this algorithm to achieve the research goals. In reference [19], the authors used the AES algorithm to encrypt information and create an encrypted data block between IOT components. They introduced this method as the most secure symmetric key encryption method. In the present study, however, the data block chains are created based on the same method and the feedback chaining method has been chosen for this purpose, because slightest alteration (even 1 bit) in data can affect the outcome of the final consensus. In reference [20], the energy consumption of IOT encrypted systems and their computing requirement are evaluated when using the AES encryption method. In this reference, the AES encryption method is introduced as the most common encryption method of IOT systems. The results confirmed that energy consumption rate and computational requirements of this method are acceptable, and it can be recognized as one of the best encryption algorithms. Speaking of computational requirements, the present study showed that AES algorithm is an efficient choice for applications related to energy industry in a smart city in order to reach a consensus between energy producing and consuming agents in the shortest possible time. Reference [21] introduced HASH and authentication methods as alternatives to symmetric encryption methods, while according to principles of cryptography, the node authentication methods are complementary to symmetric encryption methods rather than their alternatives. Reference [22] describes the practical implementation of AES encryption method, and shows that the implementation development has reached the point where quantum circuits can be designed to provide the ground for low-cost implementation of the method in order to ensure that they can resist quantum attacks by quantum computers. Reference [23] seeks to reinforce the AES method against fault-based collision attacks. In general, the AES encryption method has many applications and potentials which have significantly contributed to achievement of goals set in the present study.

The primary attributes and characteristics of this work with regard to prior works in the area can be stated as follows:

- Energy management through integration of distributed and central management in IOT platform.
- Creating a security and optimization combined protocol in cloud computing simultaneously.
- Adopting a Cipher Block Chaining method into cloud computing for dispatching data in a way that don't get disturbance to competitive energy market.

The remaining sections of the paper are as follows. Section II refers to the IoT structure based on the AES security algorithm. approach definition. Section III represents the proposed energy management within smart city. The sections IV and V describe the PSO method along with the uncertainty model. Finality, the relative Results are indicated in section VI and the work is concluded in the last section.

II. IoT ARCHITECTURE AND SECURITY PROTOCOL

Energy management gets objectivity through the IoT-bed concept. IoT is by definition a generic concept that involves various aspects. In general, a comprehensive definition can mention for IoT is accessibility and wide communication feature of programmable devices in wireless and remote-control systems. This study makes a proper energy management capital out of IoT advantages for achieving optimal consensus among producers and consumers for a satisfactory and stable energy supply with low-cost operation. The IOT architecture includes several parts in this investigation that the pseudocode in Fig.1 and Table I describes it. All agents containing transportation, smart grid, microgrids, DERs, energy hub systems, and demand possess IOT devices for sending data in the lowest level of IOT architecture. In the middle level of IOT architecture executed sending protocol by feedback block-chaining method while the encryption approach is AES algorithm. This level splice agents to cloud computing center for presence in the competitive energy market through the sequence of blocks of data. The reason for the high strength of the AES algorithm against decryptionattacks, the cyber-attacks are mostly focused on the relocation of data blocks or related bits. hence, the final consensus came under the influence, if an attack occurs. So, the agent will be put automatically aside from the competitive energy market because the energy supply of consumers takes priority in adopting this protocol. Finally, cloud computing is the tail end of IOT architecture, namely known as the decision-maker layer. Aggregator, decryption, and PSO protocols are integrated into cloud computing. The prior studies have mostly passed the data processing responsibility to cloud computing while benefiting from IOT ground for smart city management. This study but creates alliances between distributed and integrated management on IOT ground. So, this approach to energy management contains two part that executes convergently together. In the primary loop, each productive segment supervises and controls its domestic generation and demands that belong to distributed energy management way. The second loop covers macro energy management as integrated management in which agents dispatch their data to the decision-

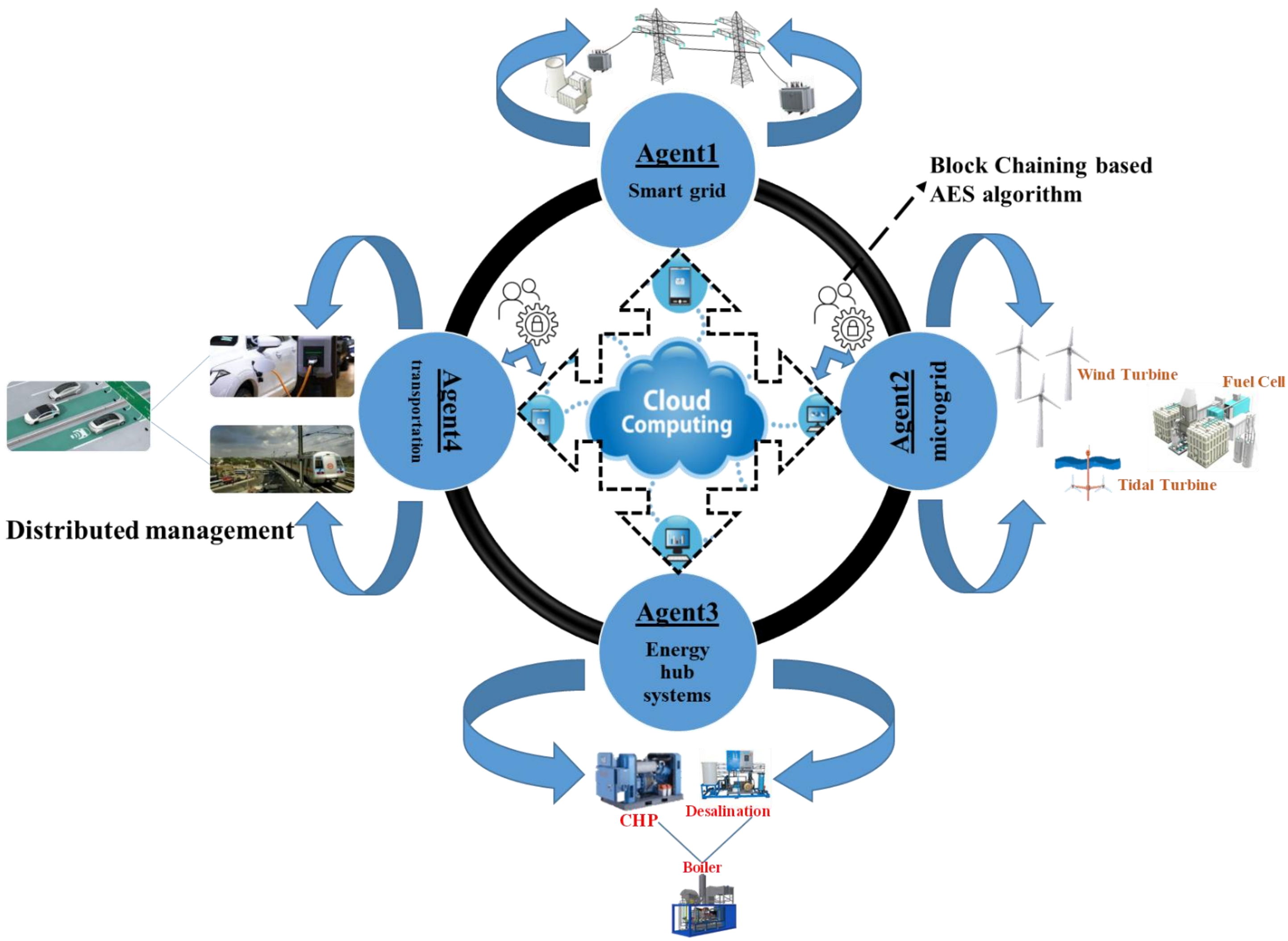


Fig. 1. Performance of the proposed method in smart city

maker center, namely cloud computing; for presence in competitive energy trading and obtains the optimal working point. AES-256 algorithm encrypts all data and builds each block. Then, each block is chained through the feedback method. Entering the blocks-chained data into the decision-maker center must be done competitively. Hence, dispatching the block-chaining data is very vital according to time protocol since the optimization through the PSO algorithm will begin simultaneously with decryption in cloud computing. Indeed, the decryption of blocks is the population in PSO. This matter has been distinctly reflected in pseudocode. The volume of data can decrease significantly; meanwhile, the final result is the same as aggregation data, and reach the time to the consensus is very lower.

TABLE I: PROCEDURE OF THE PROPOSED FRAMEWORK

1- Determine the transaction power by energy segments.
2- Encoding the transaction data by AES at each hour:
3- Cipher (byte in [4*Nb], byte out [4*Nb], word w[Nb*(Nr+1)]).
4- Begin
5- *Byte state [4, Nb].*
6- *State = in*
7- *Addroundkey (state, w[0, Nb-1])*
8- *For round =1 step 1 to Nr-1*
9- *Sub Bytes (state)*
10- *Shift Rows (state)*
11- *Mix Columns (state)*
12- *Addroundkey (state, w[round*Nb, (round+1)*Nb-1])*
13- *End for*
14- *Sub Bytes (state)*
15- *Shift Rows (state)*
16- *AddroundKey (state, w [Nr*Nb, (Nr+1)*Nb-1])*

17- *Out= state*
18- End
19- Block chaining the secured data.
20- Broadcast block through IoT.
21- execute cloud computing based on PSO algorithm.
22- For agent: 1 to n
23- Compute optimal transaction power.
25- Execute lines 4 to 19.
26- self-energy management for each agent in smart city.
27- Stopping conditions.
27- End

III. Mathematical Model of the IoT-Enabled City Energy System

Aiming to assess the proposed AES-enabled IoT decision making (AIDM) platform on the smart city, it is needed to model an energy system of the smart city here. Hence, this section is dedicated to presenting the mathematical model of the energy segments established in the smart city. It is worth noting that synergizing energy management among various systems can enhance the performance of the smart city. This is facilitated in the smart city if getting fitted out by the IoT platform. Indeed, IoT is able to carry out central energy management in reliance on the cloud environment to bring reliable synergism in the smart city. To do so, it is necessary to have access to all data related to the various energy systems which are located far apart. However, this will emerge the underlying challenges in line with the big data and security facing the IoT-enabled smart city. Let's put it this way, IoT needs to assemble information of entire energy systems to compile the central management in the cloud environment. This process makes come into being the data traffic in the wireless networks of IoT established within the smart city. The high data traffic results in the high energy consumption of sensor nodes and the high passing time for energy management within the smart city. Therefore, the central energy IoT framework may be thought-provoking to fulfill the synergism among energy systems. To overcome this, we propose an IoT-based decentralized method for the decision-making among energy systems by dint of getting the transaction data. This method enables each system in the smart city to individually conduct energy management itself with an emphasis on the transaction data received from the IoT framework. Indeed, in such a decentralized strategy, IoT is obliged to settle down only the transaction data using the particle swarm optimization (PSO)-based cloud computing among the energy systems. So to speak, making the decision on the energy transaction among systems is based on the PSO method in the cloud environment. Given the needless of all data, such a framework enables the smart city to decline the data traffic existing in the IoT platform. Fig. 1 illustrates the proposed energy framework for the smart city. To this end, we consider four energy systems including the transportation system, the hub system, the microgrid, and the main electrical grid within the smart city. These intend to perform the synergic strategy based on the proposed IoT framework aiming at operation enhancement. For better realization, the energy management related to each energy system along with the energy transaction is technically described here.

A. The electrical grid structure

As already noted, this aims to provide the fundamental formulation of the main grid. The decision-making center of the electrical grid is obliged to optimally satisfy the load demands in the first place and afterward, the generation scheduling is performed aiming to minimize the energy cost consisting of the generated active power cost, start-up, and shutdown costs. On basis of this, the objective function of the electrical grid is defined based on equation (1). It is worth noting the grid follows its objective function with an emphasis on the technical constrain including the energy balancing, min/max capacity of generators, and limitations imposed on the power line. The grid sustainability would be preserved with the aim of keeping the energy balancing in an optimal way as indicated in (2) and (3). Looking over equation (2), the energy balancing comprises three terms 1) generation units, 2) load demand, and 3) power transaction. Assume that the electrical grid is capable of exchanging power with the other systems described in the left-hand of equation (2). Similarly to that, reactive power balancing is defined by (3). Also, the energy capacity of generators is limited by equations (4) and (5). Note to forget that the generation units should consider the ramping limitations on the generated power based on equations (6) and (7) due to the demand fluctuations. Needless to say that the networking structure of the grid lines makes the ease of use of the generated power to cover the load demands. Hence, equations (8) and (9) show how the flow power of lines is modeled based on the voltage and angle of the buses that the loads and generators are located on. Imposing the limitation of the flow power on line is necessary to prevent line loading as indicated in (10) and (11). Finality, the voltage stability of the grid is one of the goals followed by energy management. Keeping this in mind, constraints (12) and (13) sustain the voltage and angles of buses within the allowed limits [24]. All in all, having looked at the synergism framework, the electrical grid can broadcast its surplus power with the transportation system, microgrid, and hub system to facilitate energy management. The synergic link among those is established in equation (2).

B. Smart transportation formulation

1) The synergic model of EVs

The EVs fill up the consumed energy arising from the trip or traffic flow on the road with the help of the parking lots connected to the electrical grid and the metro energy system. Hence, the cost/benefit of EVs is defined by constraint (14) in three parts including vehicle to grid (V2G) transaction, vehicle to metro (V2M) transaction, and denigration cost of EVs'battery. Equations (15) and (16) model how the transaction costs are calculated based on the transferred powers and price. Also, in the literature, it was proven that the high discharging cycle of the battery declines the lifetime resulting in the cost as indicated in (17). The energy balancing of EVs' batteries can be checked based on the (18) and (19) for V2G and V2M. The effect of traffic flow on energy consumption is modeled by $Vl_{p,r}$ in (20). To cover the consumed energy arising from traffic, EVs can dynamically charge the battery relying on the recharging lines $Vt_{p,r}$. The rest of the constraints related to the charging/discharging limitations of EVs are modeled by equations (21) to (29) [25].

$$C_V = C_{V2G} + C_{V2S} - \sum_{e \in \Omega^e} CD_e^d \tag{14}$$

$$C_{V2G} = \sum_{t \in \Omega^t, e \in \Omega^e} (R_{V2G_{e,t}} \times P_{e,t}^{V2G}) \tag{15}$$

$$C_{V2S} = \sum_{t \in \Omega^t, e \in \Omega^e} (R_{V2S_{e,t}} \times P_{e,t}^{V2S}) \tag{16}$$

$$CD_e^d = C_e^d \times \sum_{p \in \Omega^p, r \in \Omega^r, t \in \Omega^t} R(P_{r,e,t}^{V2G\_d} + P_{p,r,e,t}^{V2S\_d}) \quad , \forall e \in \Omega^e \tag{17}$$

- *Constraints*

$$S_{e,t}^{V2G} = S_{e,t-1}^{V2G} + P_{r,e,t}^{V2G\_c} \times \eta_c - P_{r,e,t}^{V2G\_d} \times \eta_d \quad \forall r \in \Omega^r, \forall e \in \Omega^e, \forall t \in \Omega^t \tag{18}$$

$$S_{e,t}^{V2S} = S_{e,t-1}^{V2S} + \sum_{p\in\Omega^p, r\in\Omega^r} (P_{p,r,e,t}^{V2S\_c} \times \eta_c - P_{p,r,e,t}^{V2S\_d} \times \eta_d) \tag{19}$$

$$- \sum_{p\in\Omega^p, r\in\Omega^r} z_{p,r,e,t} \times (Vl_{p,r} - Vt_{p,r}) \quad ,\forall p\in\Omega^p, r\in\Omega^r, \forall e\in\Omega^e, \forall t\in\Omega^t$$

$$S_{e,t}^{V} = S_{e,t}^{V2G} + S_{e,t}^{V2S} \qquad \forall e\in\Omega^e, t\in\Omega^t \tag{20}$$

$$P_{e,t}^{V2G} = S_{e,t}^{V2G} - S_{e,t-1}^{V2G} \qquad \forall e\in\Omega^e, t\in\Omega^t \tag{21}$$

$$P_{e,t}^{V2S} = S_{e,t}^{V2S} - S_{e,t-1}^{V2S} \qquad \forall e\in\Omega^e, t\in\Omega^t \tag{22}$$

$$u_{p,r,e,t}^{ch} + u_{p,r,e,t}^{dis} = ur_{p,r,e,t} \qquad \forall p\in\Omega^p, \forall r\in\Omega^r, \forall e\in\Omega^e, t\in\Omega^t \tag{23}$$

$$u_{p,r,e,t}^{ch} P_e^{ch,\min} \le P_{p,r,e,t}^{V2S\_c} \le u_{p,r,e,t}^{ch} P_e^{ch,\max} \quad \forall p\in\Omega^p, r\in\Omega^r, \forall e\in\Omega^e, \forall t\in\Omega^t \tag{24}$$

$$u_{p,r,e,t}^{dis} P_e^{dis,\min} \le P_{p,r,e,t}^{V2S\_d} \le u_{p,r,e,t}^{dis} P_e^{dis,\max} \quad \forall p\in\Omega^p, \forall r\in\Omega^r, \forall e\in\Omega^e, t\in\Omega^t \tag{25}$$

$$u_{r,e,t}^{ch} + u_{r,e,t}^{dis} = ug_{r,e,t} \qquad \forall p\in\Omega^p, \forall r\in\Omega^r, \forall e\in\Omega^e, t\in\Omega^t \tag{26}$$

$$u_{r,e,t}^{ch} P_e^{ch,\min} \le P_{r,e,t}^{V2G\_c} \le u_{r,e,t}^{ch} P_e^{ch,\max} \quad \forall p\in\Omega^p, r\in\Omega^r, \forall e\in\Omega^e, \forall t\in\Omega^t \tag{27}$$

$$u_{r,e,t}^{dis} P_e^{dis,\min} \le P_{r,e,t}^{V2G\_d} \le u_{r,e,t}^{dis} P_e^{dis,\max} \quad r\in\Omega^r, \forall e\in\Omega^e, \forall t\in\Omega^t \tag{28}$$

$$S_e^{\min} \le S_{e,t}^{V} \le S_e^{\max} \qquad \forall e\in\Omega^e, t\in\Omega^t \tag{29}$$

2) *The synergic model of the metro system*

As mentioned already, the requirement for the metro system can be settled down through the bilateral contract with the grid. Hence, the energy utility model of the metro system is defined based on the equation (30). It includes two parts: 1) the energy benefit arising from the braking energy transaction to the grid (31) and 2) the energy cost related to the purchase of energy from the grid to satisfy the metro's load (32). The effect of the received power of the grid on the metro's load is modeled by equation (33) for each charging station *p* at *t*. Likewise, the energy management of the metro system is allowable to broadcast the power ranging from the braking energy as indicated in (34).

$$C_{S2G} = C_{SG} - cost_{Subway} \tag{30}$$

$$C_{SG} = \sum_{p\in\Omega^p, t\in\Omega^t} (C_{p,t}^{SG} . P_{p,t}^{S2G}) \tag{31}$$

$$cost_{Subway} = \sum_{p\in\Omega^p, t\in\Omega^t} (C_{p,t}^{GS} . P_{p,t}^{G2S}) \tag{32}$$

$$L_{p,t}^{newsubway} = L_{p,t}^{subway} - P_{p,t}^{G2S} \quad \forall p\in\Omega^p, \forall t\in\Omega^t \tag{33}$$

$$P_{p,t}^{S2G} \le P_{p,t}^{BE} \qquad \forall p\in\Omega^p, t\in\Omega^t \tag{34}$$

Conformity to the M2G, the metro system can also be in contact with EVs through the charging power (as a load demand) and discharging power (as a supplement). So, the utility model for the power transaction between the metro system and EVs can be defined by (35). Also, speaking on limitations in the previous mode is true for equations (36) and (37).

$$C_{S2V} = \sum_{p\in\Omega^p, r\in\Omega^r} R_{S2V_{e,t}} \times (P_{p,r,e,t}^{V2S\_c} - P_{p,r,e,t}^{V2S\_d})$$

$$\forall p\in\Omega^p, r\in\Omega^r, \forall e\in\Omega^e, \forall t\in\Omega^t \tag{35}$$

$$P_{p,r,e,t}^{V2S\_c} \le P_{p,t}^{BE} \qquad \forall p\in\Omega^p, r\in\Omega^r, \forall e\in\Omega^e, \forall t\in\Omega^t \tag{36}$$

$$L_{p,t}^{newsubway} = L_{p,t}^{subway} - \sum_{r\in\Omega^r, e\in\Omega^e} P_{p,r,e,t}^{V2S\_d} \quad \forall p\in\Omega^p, \forall t\in\Omega^t \tag{37}$$

C. *The synergic model of the Hub system*

The hub system is able to supply three energy layers including electricity, heat, and water along with the energy converters. Meanwhile, the generation units in the hub system based on the energy layers comprise *1)* CHP (power output) unit, power transformer, and storage unit (electrical layer) *2)* CHP (thermal output) and boiler units (heat layer) *3)* desalination unit (seawater) and the water grid. also, the decision-making center of the hub system is adhered to satisfy the corresponding loads in each layer so that the objective function is minimized. To this end, the objective function of the hub system is defined based on two terms consisting of the transaction cost and the generation cost for three layers in the system. As can be seen in equation (39), the generation cost is a summation of the energy costs arising from the heat, electrical, and water units with the corresponding prices. On the other hand, the hub system is involved in the surplus cost for the energy interaction with the other systems in the smart city defined by equation (38). Also, the total cost of the hub system is indicated in (40). The relative constraints to the power transaction of the hub system and the storage's power in *t* are modeled in (41)-(42) which will limit the power generation in the nominal capacity. The energy level of the battery during *t* is determined by (43) and the charging/discharging powers of the battery are kept in (44) and (45). The power balancing in the electrical layer of the hub system is defined based on the power generations in the right-hand and load demands in the left-hand of equation (46). In this way, the heat balancing is modeled by (47) with an emphasis on the thermal generations through the CHP and boiler units. The gas amount consumed by the thermal units is received by (48). The power conversion constraints in the hub system are demonstrated in (49)-(51). As the water layer in the hub system, it is necessary to consider the equalization equation (52) to serve the water demand of the grid. It's worth noting that the water demand can be satisfied either by the water grid or the water desalinated by the chemical change unit. In order to the timely use of water in energy management, it is stored in the tank at time *t*. Likewise, the capability of the water tank is limited by constraints (53) - (55). The amount of seawater desalinated by the chemical change unit is represented in (56) - (57). The power consumption of the desalination unit based on seawater is additionally computed through the constraint (58).

$$cost_{transaction} = \sum_t (P_t^{EHUB}) \times price_{Grid} \tag{38}$$

$$cost = \sum_{t\in\Omega^T} \begin{pmatrix} P_t^{CHP} \times price_{CHP} + P_t^{Boi} \times price_{Boi} + \\ P_t^{El} \times price_{El} + \\ S_t^{bat} \times price_{bat} + W_t^{Grid} \times price_{Water} \end{pmatrix} \tag{39}$$

$$cost_{Hub} = cost_{transaction} + cost \tag{40}$$

$$\underline{P}_t^{EHUB} \le P_t^{EHUB} \le \overline{P}_t^{EHUB} \qquad ,\forall t\in\Omega^t \tag{41}$$

$$\underline{S}^{Batt} \le S_t^{Batt} \le \overline{S}^{Batt} \qquad ,\forall t\in\Omega^t \tag{42}$$

$$S_t^{Batt} = \left(1 - \alpha_e^{loss}\right) S_{t-1}^{Batt} + P_t^{chBatt} - P_t^{dchBatt} \qquad ,\forall t\in\Omega^t \tag{43}$$

$$\frac{1}{\eta_e^{chBatt}} \underline{P}^{Batt} I_t^{chBatt} \le P_t^{chBatt} \le \frac{1}{\eta_e^{chBatt}} \overline{P}^{Batt} I_t^{chBatt} \quad \forall t\in\Omega^t \tag{44}$$

$$\eta_e^{dchBatt} \underline{P}^{Batt} I_t^{dchBatt} \le P_t^{dchBatt} \le \eta_e^{dchBatt} \overline{P}^{Batt} I_t^{dchBatt} \quad \forall t\in\Omega^t \tag{45}$$

$$P_t^{eEH} = \eta_e^T P_t^{EHUB} + \eta_{chp}^{GtoE} P_t^{Gas_{chp}} + P_t^{dchBatt} - P_t^{chBatt} \quad \forall t\in\Omega^t \tag{46}$$

$$P_t^{h_{EH}} = \eta_{chp}^{GtoH} P_t^{Gas_{chp}} + \eta_{boi}^{GtoH} P_t^{Gas_{boi}} \quad ,\forall t\in\Omega^t \tag{47}$$

$$P_t^{GasIN} = P_t^{Gas_{chp}} + P_t^{Gas_{boi}} \qquad ,\forall t\in\Omega^t \tag{48}$$

$$\eta_e^T P_t^{EHUB} \leq \bar{P}^{Tr} \qquad ,\forall t \in \Omega^t \tag{49}$$

$$\eta_{chp}^{GtoH} P_t^{Gas_{chp}} \leq \bar{P}^{CHP} \qquad ,\forall t \in \Omega^t \tag{50}$$

$$\eta_{boi}^{GtoH} P_t^{Gas_{boi}} \leq \bar{P}^{Boi} \qquad ,\forall t \in \Omega^t \tag{51}$$

- *Secondary stage constraint*

$$V_t^{ST} = V_{t-1}^{ST} + W_t^{OD} - W_t^{Out} \qquad t \in \square^T \tag{52}$$

$$\underline{V}^{ST} \leq V_t^{ST} \leq \bar{V}^{ST} \qquad t \in \square^T \tag{53}$$

- *Primary stage constraint*

$$V_t^{DT} = V_{t-1}^{DT} + W_t^{ID} - W_t^{OD} \qquad t \in \square^T \tag{54}$$

$$0 \leq V_t^{DT} \leq \bar{V}^{DT} \qquad t \in \square^T \tag{55}$$

$$\underline{W}^{ID}.I_t^D \leq W_t^{ID} \leq \bar{W}^{ID}.I_t^D \qquad t \in \square^T \tag{56}$$

$$0 \leq W_t^{OD} \leq \bar{W}^{OD} \qquad t \in \square^T \tag{57}$$

$$P_t^{Des} = W_t^{ID}.CF^{Des} \qquad t \in \square^T \tag{58}$$

D. Microgrid

As noted already, the microgrid system is defined as another part of the energy system within the smart city, the modeling of which is important to be stated. The studied microgrid includes the WT, PV, tidal turbine, and fuel cell units along with the storage unit to cover the generation fluctuation. The objective function in the microgrid is shown in (59) in line with the investment cost. It is clear that the power balance relation in the microgrid is defined considering the power generated by the renewable energy units as indicated in (60). The generated power output related to the PV unit is modeled by (61) based on sun radiation DNI [26]. Also, the output power of the WTs concerning the wind speed fluctuation is calculated by (62) [27]. Based on the literature, the energy stored in tide can be utilized for the supplement of load that output power of this unit is modeled by (64) considering the current speed. It is worth noting that the protein exchange membrane fuel cell (PEMFC) may be the best among the various types of fuel cell systems in the literature. Such a unit to generate power needs hydrogen H2. The hydrogen value considering the fuel cell's output power is defined by (65). Finally, the modeling of the storage's output power in the microgrid is resented in (63) considering the charging/discharging states [24].

- *Objective functions*

$$Cost_{Microgrid} = \sum_{t \in \Omega^t} (P_t^{PV}) Price_t^{PV} + (P_t^{WT}) Price_t^{WT} + (P_t^{bat}) Price_t^{bat} + (P_t^{Td}) Price_t^{Td} + (P_t^{FC}) Price_t^{FC} \qquad \forall t \in \Omega^t \tag{59}$$

- *Constraints*

$$P_t^{Microgrid} = P_t^{Td} + P_t^{FC} + P_t^{PV} + P_t^{WT} + P_t^{bat} \qquad \forall t \in \Omega^t \tag{60}$$

$$P_t^{PV} = \frac{DNI \times C_t^{PV}}{G} \times (1 - lossPV) \qquad ,\forall t \in \Omega^t \tag{61}$$

$$P_t^{WT} = \frac{1}{2} \rho A (SWT_t)^3 \qquad ,\forall t \in \Omega^t \tag{62}$$

$$P_t^{bat} = P_{t-1}^{bat} + P_t^{cbat} - P_t^{dbat} \qquad ,\forall t \in \Omega^T \tag{63}$$

$$P_{i,t}^{tidal} = \begin{cases} 0 & 0 \leq V_{i,t} \leq V_{rated} \\ 0.5 H_{pc} \rho_s A_{tidal} V_{i,t}^3 & V_{cutin} \leq V_{i,t} \leq V_{rated} \\ P_{raded}^{tidal} & V_{rated} \leq V_{i,t} \end{cases} \qquad ,\forall t \in \Omega^T, \forall i \in \Omega \tag{64}$$

$$Hg_2^t = (P_t^{FCell} + P_t^{Cell\_B}) \times \frac{3.6 \, {}^{MJ}\!/\!{}_{kWh}}{119.96 \, {}^{MJ}\!/\!{}_{Kg}} \qquad \forall t \in \Omega^T \tag{65}$$

IV. Particle Swarm Optimization Approach

The particle swarm optimization (PSO) method is inspired from the behavior of birds flying based on the united regularity. Such a method can be utilized to minimize/maximum the objective function which is followed by the energy system. An optimizer using PSO undertakes to engender a population of particles and afterward iteratively updates the particles' speed regarding the best particle's performance. The population generated makes up of many particles moving in line with a m-dimensional space aiming to present the acceptable solutions. In such an algorithm, the particles must adjust their locations based on two factors:1) self-experience (P_{best}) and 2) the experience of self-neighbors (G_{best}). This experience includes the current location, the current velocity, and the most desirable previous location. In addition to that, to enhance the algorithm's convergence, this process will be updated based on the worst experience associated with each particle [23]. This adding term cam help particle identify the promising solution space in a more effective way. Keeping these in mind, the velocity and location of *ith* particle can be updated below:

$$v_i(k+1) = w v_i(k) + c_1 \times r_1 \times (P_{best} - x_i(k)) + c_2 \times r_2 \times (G_{best} - x_i(k)) + c_3 \times r_3 \times (x_i(k) - P_{worst,i}) \tag{66}$$

$$x_i(k+1) = x_i(k) + \alpha v_i(k+1) \tag{67}$$

Wherein $v_i(k)$ is defined as the velocity of *ith* particle with the population size of P, *kth* iteration. P_{best} is the best previous solution; G_{best} is the best previous solution among all particles, P_{worst} is the worst previous solution. Also, the particle location is updated by equation (51) wherein $x_i(k)$ is the location of *ith* particle. The adjusting parameters are c_1, c_2, and c_3; The parameters of r_1, r_2, and r_3 are randomly generated between 0 to 1. α is the learning factor in the updating process. The inertia weight of *w* is necessary to consider the updated features to the iteration *i+1*.

V. Uncertainty Model

Having a reliable decision-making center in the city energy system can highlight the synergism framework's effectiveness. This work is achieved if exactly considering the input parameters used in energy management. Keeping this in mind, it is necessary to be obtained the changeless model of input parameters existing in the energy system. Hence, this section is dedicated to providing the UT-based uncertainty model for the city energy system with the aim of having reliable energy management. To do so, this model provides a converting environment between the probability/discreet spaces for the points randomly generated. Getting inserted these points saved in matrix X into the function $T = \hat{f}(X)$ can be calculated the outputs with an emphasis on their variance and mean *C, M*. the gradual trend of the UT model's performance is defined below:

Step 1: generate points based on the variance and mean with (68) - (70).

$$X^0 = M \tag{68}$$

$$X^{k} = M + \left(\sqrt{\frac{p}{1-W^{0}} Y_{aa}} \right)_{i} \quad i = 1,2,...,p \tag{69}$$

$$X^{k+c} = M - \left(\sqrt{\frac{p}{1-W^{0}} Y_{aa}} \right)_{i} \quad i = 1,2,...,p \tag{70}$$

Y_{aa} is indicated as the covariance matrix and $\bar{R} = M$.

Step 2: calculate the Weight of point with (54):

$$W^{k} = \frac{1-W^{0}}{2p} \quad i = 1,2,...,2p \tag{71}$$

Step 3: by inserting these points into the function, the results are obtained.

$$\bar{T} = \sum_{i=0}^{2p} W^{i} T^{i} \tag{72}$$

$$C_{TT} = \sum_{i=1}^{2p} W^{i} \left(T^{i} - \bar{T} \right) \left(T^{i} - \bar{T} \right)^{R} \tag{73}$$

VI. SIMULATION AND EVALUATION

Revolution of the energy management aiming to enhance social welfare in the smart city can eventuate in the synergism model among the various energy systems. Meanwhile, it seems the proposed IoT-enabled energy management not only do bring up social welfare but the challenges related to big data and security. To prove the truth of the matter, this section is dedicated to performing the proposed strategy on the studied city energy system including four energy segments:

1) IEEE 24 buses-based electrical grid.
2) the transportation system consisting of 6 EV fleets along with 6 charging stations.
3) Hub system comprising the thermal units of CHP and boiler, desalination unit, water tank, and battery unit.
4) microgrid system with various kinds of renewable energy units including PV, WT, and tidal units.

It is worth pointing out that each energy segment in the smart city is committed to satisfying a special corresponding load, details of which were derived from [24] and [25]. Also, data related to the number of EVs, charging/discharging capacities, and their speeds in detail originated from [26], [27]. The capacities of the generation units in the hub system are similar to one specified in reference [24] concerning three energy carriers of water, heat, and electricity. As the last segment of the smart city, operating the renewable energy units in the microgrid is accomplished by getting the primary values of the wind speed, tidal current, and sunlight stated in [24]. Having these, we executed the energy management structure of the smart city regarding two different strategies in accordance with the proposed/central models. We here utilized GAMS to perform the energy management of energy segments as well as MATLAB software for central computing. The Personal Computer (PC) used in simulation has the acceptable characteristics with 64 GB of RAM. On account of involving the proposed strategy in several significant issues, it needs to be checked up on various technical aspects in relation to the security data and energy management. Hence, we analyze the consequences made up of the simulation in three forms below is an outline of those:

Case I: Comparing the PSO-IoT energy community in the smart city
Case II: Evaluating the data traffic rate in the proposed AES-secured IoT platform
Case III: Analyzing the uncertainties of the city energy system

A. Comparing the PSO-IoT energy community in the smart city

The IoT-based energy synergism proposed for energy management in smart high-wrought cities can guarantee facilitation along with economic management as well. This statement would be vindicable if getting compared with the general framework stabilized in the literature. Hence, we considered two frameworks for better clarification: *1) the proposed framework and 2) the general framework*. The latter is necessary to be more elucidated here. As noted already, to conventionally put up energetic interoperability in the city, they must broadcast the high rate of their data to the decision-making center through the wireless network established overall city. It undertakes to take out them with the goal of providing optimal energy management. Following this, the enforceable instructions would be returned to each energy segment in response to the objective function optimization as well as load satisfaction. Despite the exactly solvable management, the data security might be en prise owing to the high rate of sharing data within the general framework. This argument will be future elucidated later on. Meanwhile, the proposed framework can be a worthy alternative as a quick fix to cover challenges facing the general one. While it seems to be capable of bringing economic management in the same. To prove the truth of the matter, in this section, we executed the energy management of the studied smart city based on both strategies. Also, we compared the outcomes resulting from both strategies for each energy segment established in the smart city. Hence, Figs. 2-10 and Table II indicate the comparative outcomes of the simulation. Having looked at the proposed strategy, the segments are allowed to operate the energy management on one's own with an emphasis on the transaction data received from the IoT-based decision-making center. So to speak, such a decision-maker is amenable to only performing the convergence algorithm of taking decisions on the power transaction among those segments. It is worth pointing out that the exchange process would be converged in a tolerant way with the segments' goals. As can be seen in Fig. 2, the power exchange between the electrical grid and the hub system was brought for the proposed/general strategies at all hours. It is clear that the process of exchanging power for the proposed method took slight fluctuations during 24 hours in comparison with the general one. This would be yielded owing to the self-reliance energy management for each segment of the smart city. Of course, worth a mention is significant that these differences in the exchanging process between the general/proposed strategies have no matter for energy segments. However, the objective functions for both strategies must result in the same way. This speak can be vindicable for how to transfer power between the hub system and the microgrid as illustrated in Fig.3. Looking over the transportation system, the EVs can connect to the electrical grid through 6 number of charging stations established over the city. The energy management of the transportation system was executed based on both strategies and the results arising from the power transaction can be seen in Fig.4. On account of the traffic flow on the roads, most EVs had a tendency toward charging the battery's energy most of the time.

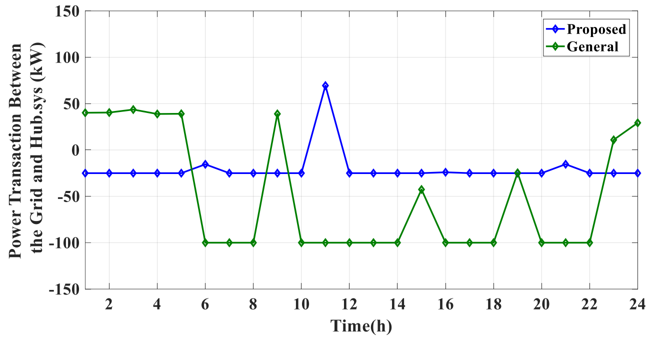


Fig. 2. Comparative result for the grid and hub system.

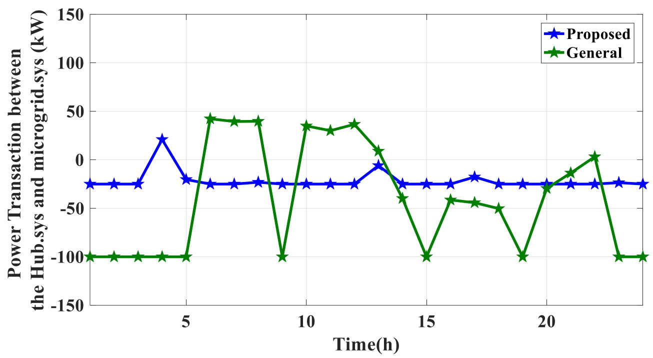


Fig. 3. Comparative result for the hub and microgrid system.

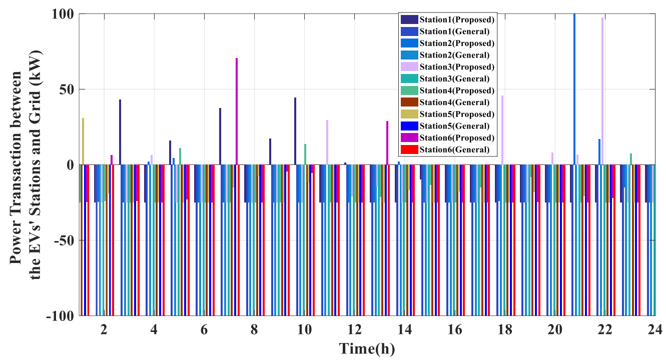


Fig. 4. Comparative result for the grid and transportation system.

Now is the time to assess the inner performance of energy segments under both strategies. We decided to elucidate in detail how the microgrid and the hub system would be operated regarding information received from the decision-making center. Hence, Figs. 5 and 86 are related to the energy management synergized three energy layers within the hub system. As noted already, the CHP unit is able to convert the gas input to the thermal/electrical energies concerning the relative conventional coefficients. We checked the performance of the CHP unit for the proposed/general strategies by looking at Fig. 5. It is explicit that the CHP unit got analogous output towards the proposed/general strategies which means being trustworthy the proposed one. This consequence is vindicable by focusing on the analysis of water management as indicated in Fig. 6. The results of the microgrid can be seen in Figs. 7-9. Looking over Fig.7, the tidal turbine output experienced a slight tolerance of 15% resulting from the comparison between strategies. This speak is correct to some extent for the PV output based on Fig. 8. But, the performance of WT illustrated in Fig. 9 was unaltered under both strategies. As stated above, the energy cost related to the segments as the evaluation criteria can be evidence of being trustworthy in the proposed strategy. Meanwhile, Figs. 10(a), (b), and (c) show the energy cost for all energy segments defined in the structure of energy management. The microgrid and hub system experienced slight tolerances of 3.2% and 2.28 % following the comparative result of the proposed/general methods. Also, this tolerance was 0% for the transportation system. All in all, the total cost of the studied smart city was inserted in Table II with a tolerance of 2.2% for both strategies.

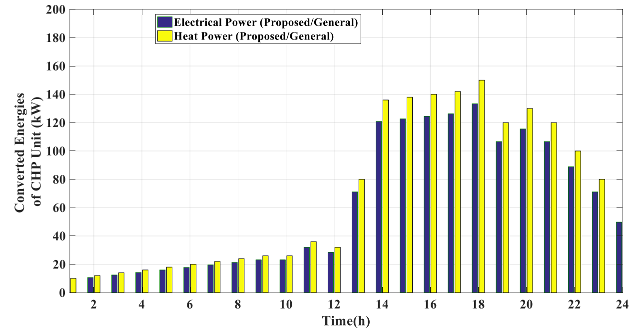


Fig. 5. Heat/electrical Outputs of CHP unit

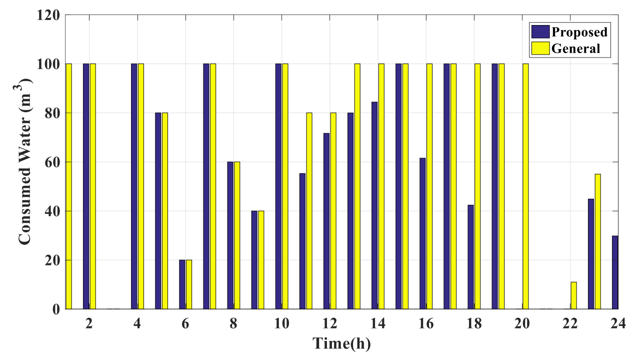


Fig. 6. The water consumption of hub system.

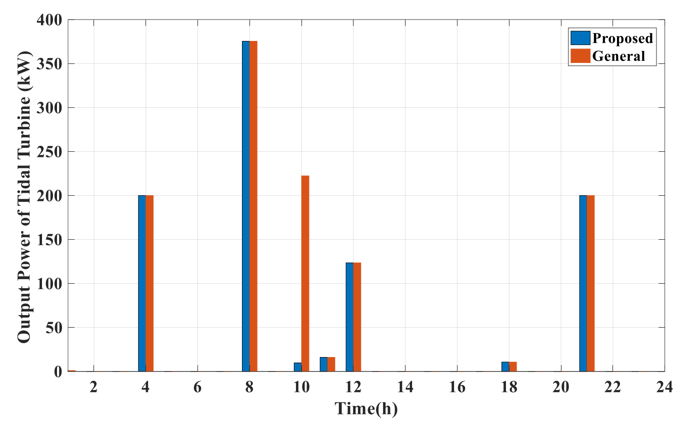


Fig. 7. The generated power of tidal turbine.

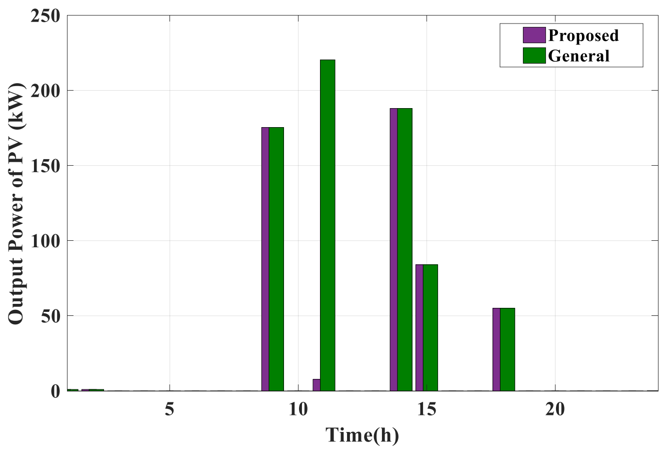


Fig. 8. The generated power of PV.

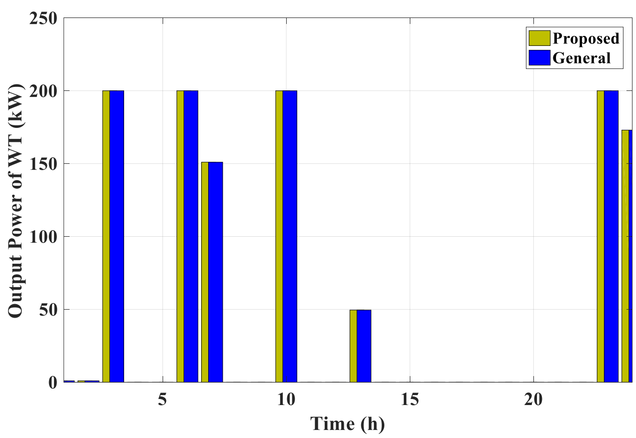
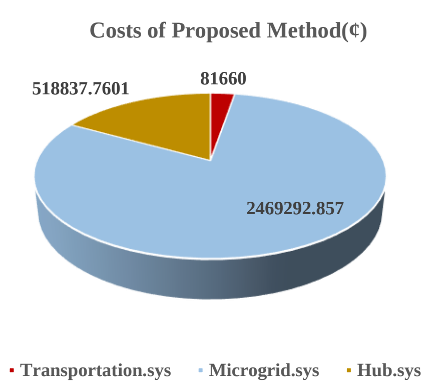
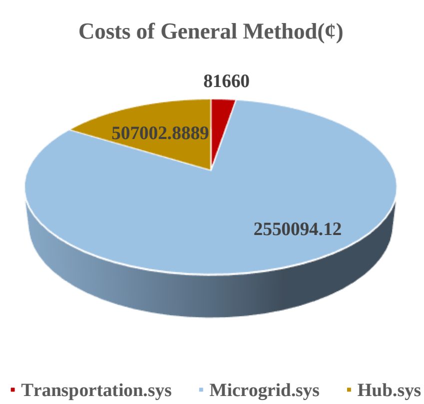


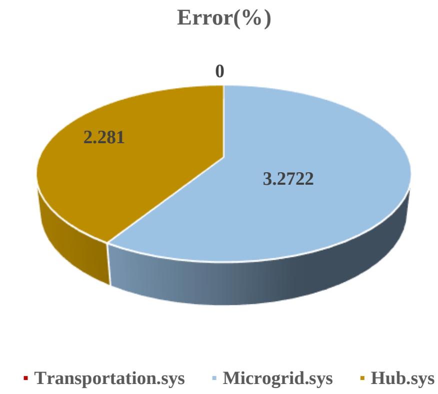
Fig. 9. The generated power of WT.



(a)



(b)



(c)

Fig. 10. The costs: a) the proposed method b) general method c) error percentage.

TABLE II: THE COMPARATIVE RESULTS OF THE COST ANALYSIS

Cases	Total (Hub.sys, Microgrid.sys, and Transportation.sys Plus Grid)
Proposed Energy Cost (¢)	111994279374.642
General Energy Cost (¢)	111994441785.181
Error (%)	2.2%

B. Evaluating the data traffic rate in the proposed AES-secured IoT platform

The goal of the AIDM strategy for the smart city is the alleviation of the data traffic rate in an invulnerable way. So to speak, in such a platform, the segments undertake to send/receive only their energy transaction data to/from AIDM aiming at energy management. Hence, the data transferred by AIDM involves low bandwidth in comparison with the general platform. While the results related to energy management would be the same as the general outcomes as proven in the previous section. This section aims to assess the performance of AIDM against the cyber-attacks launched at the convergence process of energy cost in the smart city. Indeed, we want to know whether the AIDM for the various attacks can converge the energy management in the same with the general one or not. As mentioned earlier, the AES algorithm embedded into AIDM has the ability to securely encrypt the data before sending it to the segments. Attackers try to routinely lead astray the segments using the output cipher alteration or the change in the order of changing blocks. However, the change in the encrypted data will be transpired when decrypted by the segments. Also, on account of the conditional sequence in blocking, the segments can detect the change in the order of changing blocks at all times. To prove the trustworthiness of AIDM, we considered three attacks during the convergence process based on AIDM at t=5, 14, and 24, respectively. We also executed the AIDM platform for the studied smart city based on two cases:*1)* normal and *2)* under attack. By doing this, the comparative results associated with the performance of AIDM under cyber-attacks can be seen in Figs. 11-12. In the first place, we run AIDM with any attack and indicated the convergence process of energy cost in Fig. 11. As highlighted, the energy cost had a tendency toward a linear descending way as increased the iteration due to the energy management optimization. This procedure would continue up to the optimal energy cost of 1.11994×10^{11}. By launched attacks, the detection process based on the binary signal was shown in Fig. 12. It is necessary to say here that binary signal *1* means the attack occurrence and vice versa. So, looking over the result, AIDM could detect the cyber intrusions by feeding back signal *1* as an attack alarm for *t=5, 14,* and *24*. In such disrepair, the converging process of the energy cost was outside the linear descending way in comparison with the normal state. These changes in the convergence process were highlighted in iteration 10. But, despite these changes, as the number of iterations increased, so do the energy cost close to the corresponding value in the normal state. Looking over the figure, the energy cost under attack conditions was 1.119957×10^{11}, while it was 1.119956×10^{11} for the normal state in the same iteration 20. It is clear the error was going toward zero with the increase of the iteration. In this section, we also would indicate the effectiveness of AIDM on declining the data traffic rate in comparison with the general method. Hence, Table III illustrated the comparative outputs associated with the data rate resulting from each segment for the proposed/general methods. As is evident, the AIDM platform led to a decline of 51.3%, 79.61%, 74.5%, and 57.88% in the data rate for all segments compared with the general one. This resulted owing to the reduction of the transaction data rate by the AIDM platform.

TABLE III: THE COMPARATIVE RESULTS OF THE DATA MANAGEMENT

	Dataset												
	Hub.sys			Transportation.sys			Microgrid.sys			Grid.sys			
Cases	Load Data Rate (MB)	Power Generation Data Rate (MB)	Power Transaction Data Rate (MB)	Load Data Rate (MB)	Power Generation Data Rate (MB)	Power Transaction Data Rate (MB)	Load Data Rate (MB)	Power Generation Data Rate (MB)	Power Transaction Data Rate (MB)	Load Data Rate (MB)	Power Generation Data Rate (MB)	Power Transaction Data Rate (MB)	Total Rate (MB)
Proposed Method	-	-	6.144	-	-	18.4۳	-	-	6.144	-	-	24.۰۱	55.292
General Method	12	۱٥	6.144	۱۸	٥٤	18.4۳	۳	۱٥	6.144	۳	۳۰	24.۰۱	۲۰٤,۷۲
Error (%)	81.3%			79.61%			74.5%			57.88%			72.99%

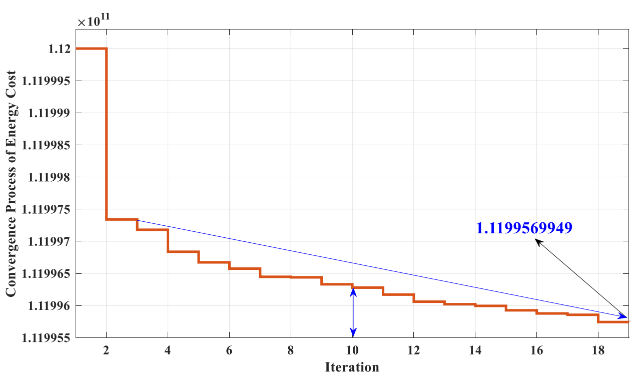
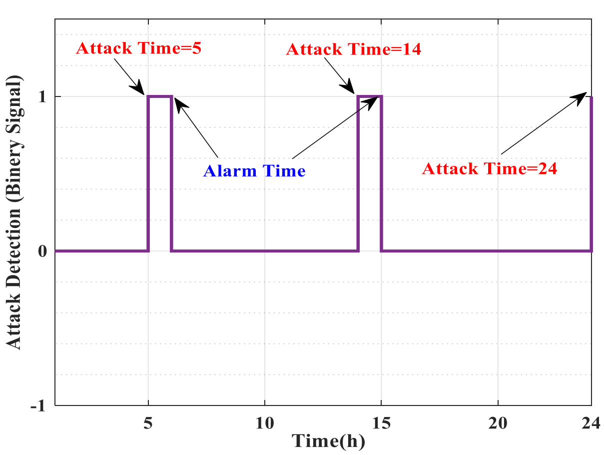
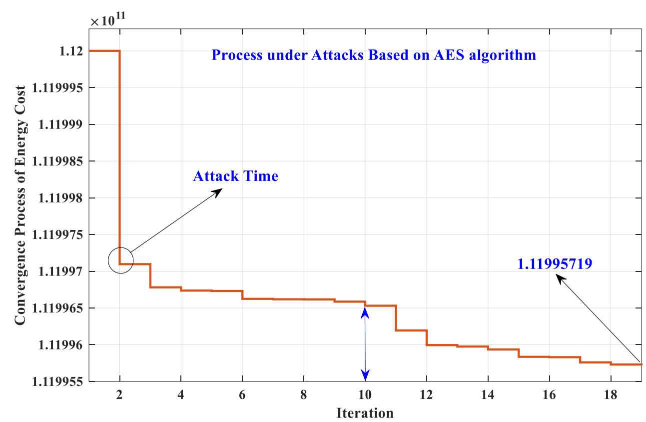


Fig. 11. The consensual energy cost of studied smart city based on the proposed method without cyber-attacks.



(a)



(b)

Fig. 12. The consensual energy cost of studied smart city based on the proposed method with two cyber-attacks at various hours: a) detected the cyber attacks by AES algorithm b) convergence process of energy cost.

C. *Analyzing the uncertainties of the city energy system*

Having a close look at the uncertainty of energy management can help enhance optimal decision-making. Indeed, due to the doubtful changes in the input parameters of the system, energy management would be slippery that needs to deal with. To this end, it seems the UT model can cover the uncertain parameters existing in the system. This section provides detail on how the uncertainty model affects the performance of the city energy system. On account of the high uncertainty existing in the transportation system, we checked only the uncertain effects on the charging/discharging powers of EVs. Hence, we executed the UT model on the transportation system and provided the relevant results by Figs. 13-14. The charging/discharging powers for all EVs based on the deterministic model were shown in Fig. 13. This analysis was brought based on the uncertainty model in Fig. 14. As can be seen, the EVs based on the uncertainty model experienced the marketed fluctuations of 10%, 21%, 20.3%, 22%, 4% and 15% in comparison with the deterministic one. These changes indicate the effectiveness of the uncertainty model on the energy system.

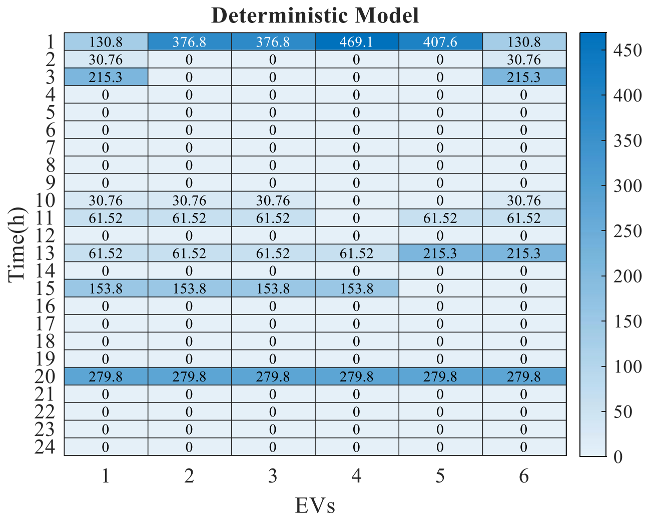


Fig. 13. The outcome of deterministic energy management in smart city.

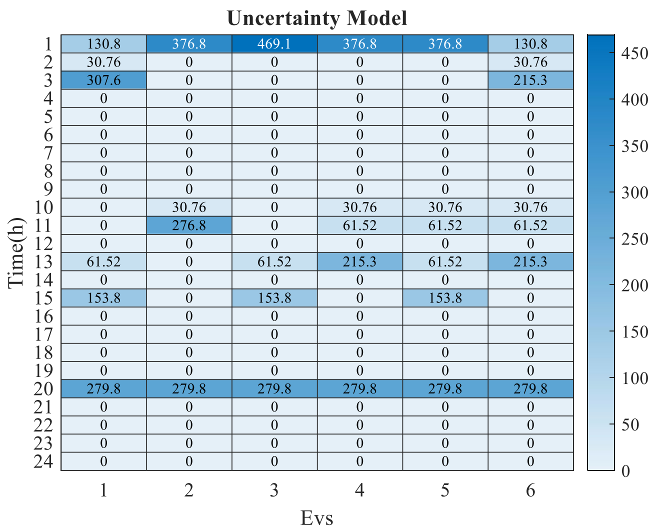


Fig. 14. The outcome of uncertainty energy management in smart city.

VII. Conclusions

This paper provided an efficacious IoT based decision making platform for the smart city energy management followed three underlying challenges: 1) alleviate the data traffic rate 2) optimal energy consensus among various segments of smart city 3) security data. Actually, we proposed a cloud computing model inspired by PSO approach for the IoT platform aiming to catch an energy concurrence among the transportation system, hub system, the electrical grid integrated with microgrid. In such a decentralized strategy, as energy segments could bring up self-energy management, their transaction data were only broadcasted through IoT platform whole the smart city. This led to the alleviation of data traffic rate within the city energy management. Also, this platform could be robustious against the cyber attacks using the AES algorithm encoded into IoT platform. To this end, we first performed the electrical grid, hub system, microgrid and transportation system, and afterward executed a proposed energy framework based on the AES-IoT bed in the smart city. The relative results were provided in previous section. To validate our contributions, we compared the energy outcome of all segments with two approaches including the proposed method, and the general method. Inferred from results that our framework could succeed in comparison with the verified general management with slight errors of 3.2%, 2.28 % and 15%. It was while the data traffic rates for the hub system, transportation system, microgrid and the electrical grid were alleviated by 81.3%, 79.61%, 74.5% and 57.88%, respectively. This means that our proposed method could appropriately bring up the energy consensus among segments along with the low data rate within smart city.

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