A Copula-Based Secured Intelligent Dynamic-Static Energy Community Transportation System for Smart Cities

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Abstract— This paper addresses a secured co-dynamic model for the energy management of Electrical Vehicles (EVs) within the real community transportation system (RCTS). The proposed model aims to facilitate interoperability among mobile energy resources within the smart city, enabling the RCTS to model the co-dynamic-static transportation systems (TSs) simultaneously. The energy management model within the traffic flow system focuses on dynamic assignment, considering the power consumption associated with the density of moving vehicles. EVs play a key role in economically managing energy in both static and dynamic behaviors within charging stations while aligning with the current traffic flow.

To enhance data security within the smart city ecosystem, a directed acyclic graph (DAG)-based decentralized cyber security approach is recommended. This approach ensures that data transactions involving mobile energy resources are secured against cyber-attacks through the use of public, private, and transaction blocks. Additionally, an uncertainty-based copula function is presented to create a precise management environment within the smart city. The results indicate that the proposed model for transportation energy resources tends to reduce energy costs by optimally controlling energy consumption within traffic flow, compared to normal conditions.

Index Terms-- Smart city, traffic flow, real transportation energy management, co-dynamic-static analysis, DAG, copula function.

NOMENCLATURE

Sets/Indices

i : Set/index of subway's stations

k : Set/index of urban paths

h : Set/index of time

v : Set/index of EV

Constants

A Front surface area of EV

a_g, a_{gr} and c_r Gravity acceleration, road gradient and coefficient of rolling resistance, respectively

c_a Coefficient of the air drag

c_{aa} Coefficient of acceleration resistance

${C_{v,h}}^{V2G}$, ${C_{v,h}}^{V2S}$ Bidding prices of V2G, V2S

$C_v^{\deg}$ The degradation cost of EVs battery.

d_a Local interval

D Density

E_{TE}^s Traction efforts

E_{Roll}^s Force of rolling resistance

E_{Air}^s Air resistance force

E_{Grad}^s Gradient resistance force

E_{Acc} Acceleration resistance force

$E_v^{\min}$ / $E_v^{\max}$ Min/max capacity of the EVs' batteries, respectively.

h_a Time interval

N Number of vehicles

m EVs' weight

P_{TE}^S RCTS electrical power

$P_v^{\min\_c}$ /Min/max charging rate of the EVs' batteries. $P_v^{\max\_c}$

S EVs' speed

V Volume

ε_a Air density

η_c, η_d Charging and discharging efficiencies, respectively.

Variables

$cost, cost_{Subway}, cost_{EV}, , cost_{SG}$ Total, subway's demand supply ,EVs and smartgrid costs, respectively.

$cost_{\deg}$ EVs degradation cost.

$E^{V2G}_{i,k,v,h}$, $E^{V2S}_{i,k,v,h}$, $E_{k,v,h}$ EV battery capacity during V2G, V2S and total energy transactions, respectively.

$E_{k,v,h,s}$ Total energy transactions of EVs in dynamic state

$P^{V2G}_{k,v,h}$, $P^{V2S}_{i,k,v,h}$ V2G and V2S energy transactions, respectively

$P^{V2S^c}_{i,k,v,h}$ / $P^{V2S^d}_{i,k,v,h}$ Charging/discharging power during V2S, respectively.

$P^{V2G^c}_{i,k,v,h}$ / $P^{V2G^d}_{i,k,v,h}$ Charging/discharging power during V2G, respectively.

$u^c_{i,k,v,h}$, $u^d_{i,k,v,h}$ Binary variables related to the charging, and discharging of the EVs.

I. INTRODUCTION

A. Motivation and Aims

Smart city ecosystems are the next generation of cities that rely on smart information and communication technology to provide bi-directional information and energy transmission. The smart city and novel technologies such as artificial intelligence and digital twin have dramatically improved traditional cities in terms of efficiency and reliability [1]. However, with the emerging various layers of the smart city (such as smart grid (SG) and transportation systems (TSs)), the need to develop an effective decentralized management model and interoperability of these layers has become a major issue. Energy management of TSs heavily depends on their performance in the dynamic assignment. Considering the energy consumption of electric vehicles (EVs) in the dynamic state arising from traffic and travel, the behavior of EVs possesses a large influence on energy management functionality. Hence, to induce reliable management, dynamic analysis of vehicle behavior is a pivotal requirement.

B. Literature Review

With the evolution of smart cities, conventional cities have been renovated to authorize easier management, higher efficiency, and boosted reliability [2]. The smart city is an interconnected, instrumented, and intellectual circumference [3]. The phrase interconnected means the potential to integrate data and share them with different municipal services. The phrase instrumented indicates a potential to achieve different data on city life and related substructure in the real-time state by the linked instruments, sensor nodes, and measurement systems [4]. The phrase intellectual mentions information processing through optimization, modeling, and advanced analysis to make the most valid decision. Furthermore, the smart city facilitates a bi-directional exchange of information and energy between different energy layers. This not only enables the seamless transfer of energy from manufacturers to consumers but also supports real-time management processes, allowing for immediate recovery. Various energy layers such as smart transportation, SG, and smart building pose challenges from the operation and management perspective in the smart city. Particularly, the density and power changes of EVs in traffic flow are crucial criteria that should be considered in the accurate management of energy systems. Also, the presence of these energy systems associated with their related uncertainties such as energy forecasting errors and traffic density changes increases the complexity of energy management. Therefore, providing interoperability and a secure synergistic framework between different energy layers (especially TS) can address the challenges associated with energy management. With this rationale, discussions including the evaluation of TSs in the static and dynamic assignments, security framework, and uncertainty of energy systems in the energy management framework are examined in the following.

1) *Transportation system*

The novel platforms of smart TS have effectively reinforced the TS industry's perspective in terms of increased reliability, safety, and efficiency [5]. However, with the advent of smart TSs as distributed energy resources, the requirement to develop efficient, reliable, and decentralized management resolutions in the smart city framework has become a primary focus. Before presenting the real community transportation system (RCTS) model, it is necessary to study and review transportation systems (TSs) in both static and dynamic assignments. Initially, both static and dynamic assignments of TSs are studied, followed by a review of the security and uncertainty frameworks within TSs. TSs (such as EVs and subways) are the most influential and new strategies in the smart city that are hourly distributed in the current power network and they can be used as storage or consumer in the smart city [6]. The static assignment focuses on the stationary state of transportation systems such as EVs and subways when they are at the charge stations, while the dynamic assignment examines the dynamic and moving state of the EVs when they are in traffic flow. Vehicle-to-grid (V2G) and grid-to-vehicle (G2V) are innovative technologies that allow EVs and the grid to inject accumulated energy into the grid or vehicle, facilitating efficient energy exchange to enhance the operation and management of the power grid in static assignment [7], [8]. Intelligent management of these technologies can bring benefits such as modifying the peak load and reducing total prices and energy losses for all energy systems. Recent researches show promising advancement in V2G technology [9]. Some of the investigations on V2G technology and its corporation in the power network are studied in [10-12]. In [13], authors studied uncertainties associated with wind turbines

(WTs) and EVs regarding the V2G state and their impact on the power network. Subway station is introduced as new power strategies in the smart city that is known for their massive power consumption. Refs [14] and [15] present the approaches and technologies of railway stations aiming at energy consumption minimize. The energy generated from braking will significantly contribute to energy savings in the smart city. Consequently, the subway station system can function as a mobile storage and consumption unit in smart city environments. To effectively utilize regenerated braking energy, various methods such as programmable tables, power storage systems, and reversible subway stations have been explored [16]. In an effort to enhance the efficiency of regenerated braking power, an efficient schedule has been developed in [17] that fits the arrival time and the departure time of subways. This approach is devoted without the use of any power storage system known as reasonable advantages. Operating the power storage technique wayside and onboard of subways aiming to improve the service of the regenerative braking energy is discussed in [18]. Though this strategy does not need a complicated timetable, the energy storage instrument's cost and its heavy weight are the principal shortcomings of such technology. In [19], the authors introduce the concept of a reversible station strategy that enables the grid to receive the regenerative braking power of the trains. To mitigate the significant impacts of subways in the smart city and transition from a solely consuming role to an active participant, researchers have recently proposed the idea of subway-to-EV (S2V) [3]. In [6], the S2V approach by the subway station is regarded as demand (charging form) and mobile storage resources (discharging form) in the smart city's operation. The dynamics assignment of the TSs (especially EVs) is assessed when EVs move on the road. Exposure to various conditions, such as traffic flow, has led to changes in the speed of vehicles at any time, which in turn affects the process of energy consumption. In reference [20], the authors conducted a comprehensive study on the various factors influencing vehicle traffic flow dynamics and simulated them using mathematical models. To reduce energy consumption, the authors in [21] proposed a novel model based on EV traffic flow, derived from the optimal energy consumption model using the minimum principle theory. Reference [22] explored an approach to model the EV load profile under various conditions such as traffic congestion, air-conditioning, and probabilistic situations. Reference [23] concentrated on performing a comparison mechanism between the static and dynamic traffic states to evaluate congestion pricing strategies on a real traffic system. In [3], the authors addressed the power management technique in EV parking and also presented the traffic-based -model in the static state. However, the energy consumption model of EVs in dynamic and static assignments has not been studied simultaneously. Also, there is not an integrated framework that simultaneously evaluates the energy management of transportation systems in both dynamic and static assignments.

2) *Cyber-Physical Security Framework*

With the focus on data and energy transactions among distributed energy sources (such as EVs, renewable energy sources, and smart grid) and other layers, the requirement to create an efficient decentralized security framework for the smart city has become the main current [24]. Within the proposed framework, various transactions between TSs (EV and metro) and the grid underscore this necessity. In this context, considerable research has been devoted to examining security frameworks based on blockchain technology. The blockchain is the distributed ledger technology in which nodes keep a copy of the ledger, and the blocks in the ledger are cryptographically linked to each other. Authors in [6] presented the blockchain technology-based secure data transaction framework in smart cities. In [25] a framework based on blockchain has been suggested to address power security and privacy assurance in the EV-aided SG ecosystems. Researchers in [26] furnished a thorough review of the approaches and structure of blockchain. Given that in blockchain technology, data blocks are consecutively related, the possibility of invasion by third parties is still achievable. To tackle this problem, authors in [7] have presented the security of energy trading in microgrids based on the directed acyclic graph (DAG) technique. The DAG technique is a secure and reliable approach to prevent and detect various types of attacks. Furthermore, various other algorithms such as machine learning and deep learning to detect attacks in the cyber domain and other fields are currently attracting the attention of researchers [27], [28]. In [29], the authors integrated these two algorithms to improve the attack detection accuracy. In [30], a complete review of deep learning methods in the cyber field has been investigated. However, an effective security approach has not been presented in the framework of interactions of transportation systems in both dynamic and static assignments.

3) *Uncertainty framework*

It is important to note that the uncertainty of the energy systems within the smart city area is indisputable [31]. As a result, numerous studies have been dedicated to exploring a probability-based energy management platform in recent years. The various methods of probability energy management (PEM) study can be classified as numerical techniques, analytical techniques, approximate techniques, and hybrid techniques [32]. The Monte Carlo technique is one of the most widespread numerical techniques embraced for PEM problems and has also been employed for many other power system issues. This method accurately assesses the impact of input uncertainty. However, due to the vast duplicated calculations, this technique suffers a high computational burden. Method unscented transformation (UT) is one of the estimation methods that have considerably high accuracy and speed for modeling uncertainty [33]. A UT-based stochastic method was proposed for PEM in the smart city environment [3], which was able to correctly model the correlation between energy systems (such as WTs and TSs). In [34], authors proposed a new stochastic framework based on UT for modeling the stochastic behaviors of EVs and WTs with respect to the penetration of EVs and V2G technology. Considering uncertainty in the problem is crucial for achieving accurate and adaptable management performance. Table 1 offers a comparison of the literature review within the smart city sector.

TABLE 1
COMPARISON OF LITERATURE REVIEW ON SMART CITY DIFFERENT SECTORS

Reference	Methodology	Technology
[5]	Reinforcement of the Transportation System (TS) industry's perspective with novel smart TS platforms	increased reliability, safety, and efficiency
[6]	Advocates the need for efficient, reliable, and decentralized management resolutions	Real Community Transportation System (RCTS) model
[7], [8]	Intelligent management for benefits such as modifying peak load and reducing total prices and energy losses.	Vehicle-to-Grid (V2G)
[9-12]	Highlights promising advancements in V2G	V2G
[13]	Studies uncertainties associated with Wind Turbines (WTs) and EVs regarding the V2G	V2G
[14], [15]	Minimizing energy consumption.	NA
[16]	Programmable tables, power storage systems, and reversible subway stations	Regenerative Braking Energy
[17]	Develops an efficient schedule to improve regenerated braking power's efficiency without using power storage.	NA
[18]	Regenerative braking energy.	Power Storage Technique
[24]	Decentralized security framework	Distributed control.
[6]	Secure data transaction framework in smart cities	Blockchain technology
[25]	EV-aided SG ecosystems and smart contract	Blockchain technology
[7]	Directed acyclic graph (DAG) technique,	DAG
[29]	Integrates machine learning and deep learning algorithms	IDS systems

C. Contribution

This paper intends to provide a secure and accurate energy management framework derived from the interoperability of TSs and the power grid within the smart city domain. To achieve this, the paper proposes the RCTS based on the co-dynamic-static model, encompassing TSs of the smart city in an integrated framework. This model examines and models EVs in both dynamic and static assignments concurrently. Accurate traffic flow modeling plays a significant role in the energy management of TSs and other layers of the smart city, as EV speed within traffic flow varies based on traffic density, impacting EV power consumption.

All in all, the RCTS seeks to model the co-dynamic-static of transportation systems in parallel that can plan EVs management based on traffic on the road. This approach yields accurate and reliable energy management for the network and the decision-making system of transportation. Therefore, energy management in the static assignment (parking stations) is real management and its results are close to reality. This leads to appropriate analysis in a real environment, which results in reduced related costs. Put differently, the integrated modeling and analysis of transportation systems in both dynamic and static scenarios can lead to a more precise prediction of EVs performance within transportation systems. In addition, this paper provides a secure framework based on DAG to create a decentralized secure environment in different domains. The main objective is to create security of energy and data transactions among various layers. The primary justification for utilizing blockchain in the proposed model is the need for EVs to have real-time traffic flow information, necessitating a high volume of data exchanges among EVs. As a result, the manipulation and alteration of data lead to heavy traffic, resulting in high energy consumption in the TSs. Thus, it is essential to incorporate a blockchain system in the proposed framework to secure the data exchanged between EVs. Furthermore, given the uncertainties in various aspects of the TS, such as traffic density and the charging demand of vehicles, a copula function-based PEM has been introduced. Generally, various investigations have been accomplished on energy management and energy transactions between various layers of the smart city to develop energy systems functionality. In [3], the authors presented a synergistic framework between renewable energy sources and TS aiming to efficiently plan and use renewable energy sources. In other words, the integration of the grid and TSs (such as EVs and subways) aiming to manage the total energy is studied. Similarly in [7], a secured synergy mechanism in energy systems has been investigated given the uncertainty of renewable energy sources. Reference [35] presented a synergistic approach between intelligent TSs and the power grid. In [36], an energy management framework based on blockchain for transportation systems is proposed. The aim of this research is to remove threats in the TSs framework. In [37], the authors reviewed the numerical approaches applied to model the EVs aiming to assess energy consumption. The proposed model presents accurate decentralized management on various layers of the smart city which are secured with the DAG-based blockchain framework.

Intending to evaluate the different aspects of the work, and to better understand the innovations presented in this paper compared to the work presented in the literature, Table 2 can be a good guide for this work, which provides a clear view of the findings of the concerned references and it underlines the differences.

The highlights of this paper can be outlined as follows:

- Presenting a novel co-dynamic-static model of energy management based on the real community transportation system (RCTS)
- Developing an effective modified blockchain framework inspired by the DAG as a reliable, and decentralized structure for optimal energy management of the smart city

- Providing a copula function-based PEM to address uncertainties in TSs, including traffic flow and the charging demand of vehicles

The rest of this paper is organized as follows. The proposed RCTS model based on dynamic and static assignments and also the integrated energy management system of the smart city are proposed in Section II. The security framework DAG-based cyber-physical security is described in Section III. Section IV presents the copula function-based uncertainty model, and the evaluation of the results is provided in Section V. Section VI refers to the conclusion.

TABLE 2
BRIEF REVIEW OF RESEARCH UNDER STUDY

Ref.	Static transportation systems energy management	Dynamic transportation systems energy management	Co-dynamic-static energy management	Blockchain-based security	Uncertainty framework
3	✔				✔
7	✔			✔	✔
13	✔				✔
20		✔			
36	✔			✔	
Proposed Model	✔	✔	✔	✔	✔

II. REAL COMMUNITY TRANSPORTATION SYSTEM MODEL OF SMART CITY

To conceptual comprehend the proposed energy management model, Fig. 1 is provided with the aim of the methodology of the proposed framework. In an integrated energy management framework, TSs are developed in two dynamic and static assignments simultaneously. To provide an integrated management framework, first, the energy consumption model of the TS in the two mentioned assignments should be modeled, then it should be included in the proposed energy management model. As it is clear from the fig, energy management based on the dynamic model is launched at the first level. At this level, by modeling the traction energy arising from the traffic flow, dynamic energy management is implemented for each vehicle. According to equations 7 and 8, the vehicle energy consumption model is based on the average driving speed and specific power of the vehicle. In the second level, the management of static energy arising from the performance of EVs in parking stations is executed, EVs can charge/discharge themselves based on two types of parking lots. Therefore, the energy model of EVs is presented in two modes V2G and V2S according to equations (14) - (21). To provide integrated energy management, equations (10)-(13) are implemented. The proposed model is fully explained with the relevant equations in the next section. The data is transferred to the Copula model to model the complex and uncertain behaviors. Finally, the security framework is provided to create a secured data and energy transaction between carriers. With this rationale, this section is dedicated to the modeling of the RCTS based on dynamic and static assignments (first and second levels) as well as the proposed management system architecture integrated with energy systems. As mentioned earlier, the energy management system of electric vehicles relies on the traffic flow on the roads, traveling, and their stationary state. Before presenting the RCTS model in both tasks, the EV traffic flow needs to be investigated and modeled.

A. Mathematical formulation of Traffic flow

Traffic flow is caused by the specific interaction of drivers and vehicles with each other and the physical elements of the road and public environments. Because both drivers' behavior and vehicle specifications are different. Vehicles do not follow exactly similar behavior in traffic flow. Two traffic flows will not behave in exactly the same way in the same situation. In traffic, we are dealing with a variable element. Traffic flow along streets and highways varies with defined characteristics based on time and position. In describing traffic flow, key parameters must be defined and measured. Traffic flow parameters are divided into two categories: macro and micro parameters. Macro parameters that describe the traffic flow globally. Micro-parameters describe the behavior of vehicles or a pair of vehicles in traffic flow. Three of the macro parameters include:

-Volume or flow rate

- Density

-Speed

Micro parameters include:

- The speed of each vehicle

- Time interval

-Local interval

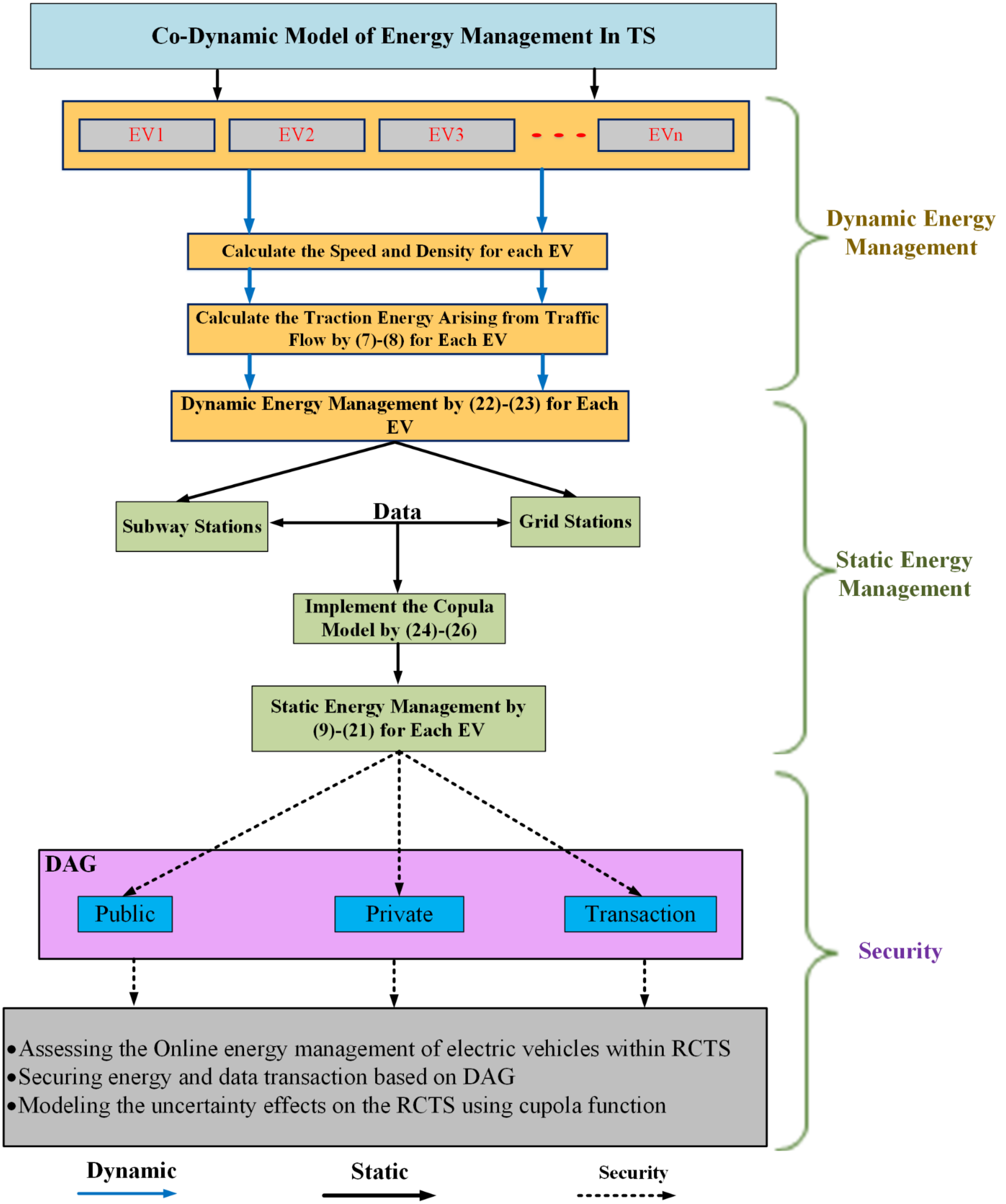


Fig. 1. The proposed framework methodology

Volume is defined as the number of vehicles (N) passing through a given length of road at a specific time (s), therefore the unit of measurement for volume is the number of vehicles per unit time. Speed (S) is defined as the rate of movement over a distance at a time unit. Density (D) is defined as the number of vehicles passing through a given length of road (x) and is expressed as the number of vehicles per kilometer. Equations (1) and (2) show flow rate and density, respectively [20]. Density is calculated by measuring the velocity and flow rate as follows:

$$V(x,s) = \frac{\Delta N_V}{\Delta s} \tag{1}$$

$$D(x,s) = \frac{V(x,s)}{S(x,s)} \tag{2}$$

The density between the three main parameters of traffic flow is the most crucial as it has the strongest correlation with traffic demand. Density serves as a critical indicator of traffic flow quality, representing the closeness of vehicles to one another. Direct measurement of density is not easy, so advanced detectors can measure occupancy, which is a relevant parameter. If a detector is embedded on the road, the time during which the detector is occupied by a vehicle within a specific period can serve as the foundation for calculating density [38]. Density is calculated as follows based on Fig. 2.

$$D = \frac{5280 \times O}{L_V + L_d} \tag{3}$$

where D is the density, L_v is the vehicle length, L_d is the length of the detector, and O is the average duration of detector detection. While flow rate, speed, and density represent macroscopic characteristics of traffic flow, they can be related to microscopic parameters that describe individual vehicles or a specific pair of vehicles in the traffic flow.

Local interval defined as the distance between consecutive vehicles in a traffic lane, is measured using various conventional points on vehicles such as the front bumper or front wheels. The Local interval is determined using density as follows [38]:

$$D = \frac{5280}{d_a} \tag{4}$$

where d_a is the distance between vehicles. The time interval (h_a) is defined as the time distance (s) between consecutive vehicles passing a point along the roadway, and is directly linked to the flow rate as follows [38]:

$$V = \frac{3600}{h_a} \tag{5}$$

where V is the flow rate and h_a is the time interval at the passing point in seconds. The average speed is determined by calculating the local distance and time interval as follows [38]:

$$S = .68\frac{d_a}{h_a} \tag{6}$$

Consequently, average speed and density are metrics calculated for a specific section of the road, whereas the flow rate is measured on a point scale.

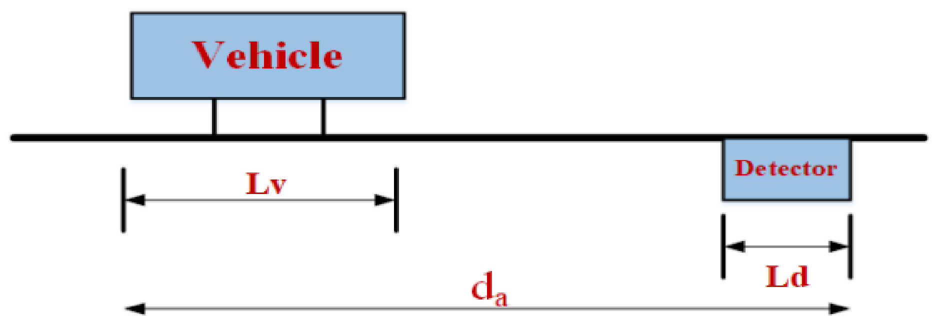


Fig. 2. Illustration of the vehicle spatial distance

B. Proposed real co-dynamic-static energy model

This paper considers the RCTS model from two points of view: the dynamic assignment and the static assignment. Route traffic is an indispensable functional factor influencing energy consumption. The congestion of traffic flow rises the driving period and lessens the driving efficiency as the EVs drive at non-economical velocities that significantly impact power consumption and the demands of charging. In this section, the actual driving conditions in both stationary and dynamic assignments are assessed. Consideration of these conditions will lead to the accurate simulation and model of the transportation systems. The dynamics model of the EVs is presented to assess the traffic flow model that affects the EV power consumption process. With this in mind, an energy consumption model is developed based on the average driving speed and vehicle-specific power (VSP) to calculate the energy consumption of the EV. The average speed is utilized to characterize the typical driving conditions of the EV over a specific period of time (seconds) [22]. The VSP represents the power output of EVs or the traction electrical power, playing a crucial role in defining the energy consumption efficiency of EVs under real operational conditions. It is important to note that different driving speeds correspond to different VSP values. Assuming the EV maintains a constant speed, the traction efforts required while the vehicle is in motion are defined as follows (7) [22]:

$$E_{TE}^{s} = E_{Roll}^{s} + E_{Air}^{s} + E_{Grad}^{s} \qquad (7)$$
$$= c_r \times a_g \times cosa_{gr}^{s} + \frac{1}{2}\varepsilon_a \times \frac{c_a \times A}{m}(S^s)^2 + a_g \times \sin a_{gr}^{s}$$

The first term is the force of rolling resistance, the second term is air resistance and the third term is in (7) the gradient resistance force that happens when the vehicle drives up the hill. a_g, a_{gr} and c_r represent the gravity acceleration, the road gradient and the coefficient of rolling resistance, respectively. ε_a is the air density, c_a is the coefficient of the air drag, and A is the front surface area of EV, S is the EVs'speed (*m/s*), and m is EVs'weight (*kg*). As mentioned, the TSs in the dynamics assignment is evaluated when EVs move on the road. Current traffic flow is led to changes in the vehicles' speed. Traffic flow is described as the number of vehicles passing through a point on the road over a specified time as formulated in (6). As mentioned, one of the principal scales of traffic flow characteristics is density, which is defined as the number of vehicles crossing a certain length of road as described previously. As revealed in Equations (5)-(6), the traffic flow model is dependent on the density parameter, and this parameter is based on speed variation. Therefore, in the proposed RCTS, in addition to the forces acting upon the EV (as described in Equation (7)), the term of the acceleration resistance force (E_{Acc}) resulting from the traffic flow is added to Equation (7). Therefore, the operation of the EV at a speed and with an acceleration (speed variation) demands a traction force F_{TE}^{S} as follows (8):

$$E_{TE}^{s} = E_{Roll}^{s} + E_{Air}^{s} + E_{Grad}^{s} + E_{Acc}^{s} \qquad (8)$$
$$= c_r \times a_g \times cosa_{gr}^{s} + \frac{1}{2}\varepsilon_a \times \frac{c_a \times A}{m}(S^s)^2 +$$
$$a_g \times \sin a_{gr}^{s} + c_{aa} \times m \times \frac{dS^s}{ds}$$

Where c_{aa} is the coefficient of acceleration resistance and gravity acceleration is 9.81 m/s2, ε_a= 1.207 kg/m3, c_r and c_a are 0.015 and 0.3, respectively. m= 1500 kg. The RCTS electrical power indicated as P_{TE}^{S}, is computed by multiplying the force $E_{TE}^{S}$and the speed of the EV.

$$P_{TE}^{s} = E_{TE}^{s} \times S^s \qquad (9)$$

C. Mathematical formulation of proposed RCTS

This section is devoted to the mathematical modeling of the proposed TS framework with dynamic and static assignments (as shown in Fig. 3) and also the energy transaction among energy layers in the studied smart city. These layers include SG and smart TSs (especially EVs and subway). According to economic policy, the main idea of optimal administration of energy is to minimize the total cost of energy systems in the smart city by handling production and consumption, also the interactive link with various energy systems. The proposed model facilitates energy exchange and fosters effective synergy among EVs, the subway, and the network within an integrated framework. To ensure optimal transactions across sectors, maximizing the profit of each sector, including energy transactions between EVs, the subway, and the smart grid, must be considered. EVs enhance their profitability through interactions with both the network and the subway. The subway's braking energy plays a pivotal role, serving as renewable energy that can supplement subway demand and represent a lucrative resource through interaction with the smart grid. In the proposed model, this presents an opportunity to exchange energy with EVs by buying and selling stored subway braking energy. In point, all available energy systems will attempt to supply their consumption. But, if the energy made by each energy system is not enough or too expensive to supply the supplying loads, next the power is received from other systems or stored in the available storage instruments. Therefore, the total cost of the smart city that is defined as an objective function includes the cost of TS (EV and subway) and the cost of SG. Mathematically, the total cost can be modeled as follows:

$$Cost = Cost_{SG} + \underbrace{Cost_{EV} + Cost_{Subway}}_{Cost_{Tran}} \tag{10}$$

In the static assignment, the EVs can exchange power with the power grid and subway to profit from the bidirectional energy transfer between EVs and other participating entities. The EVs cost is presented in (11) which includes of transmitted energy cost from EVs to the power grid (V2G) (11), the cost of transferred energy from EVs to the subway (V2S) (13), and the degradation cost of Evs' battery (14) [3].

$$Cost_{EV} = Cost_{V2G} + Cost_{V2S} - \sum_{v} Cost_{v}^{\deg} \tag{11}$$

$$Cost_{V2G} = \sum_{i,k,v,h} (C_{v,h}{}^{V2G} \times P_{i,k,v,h}^{V2G}) \tag{12}$$

$$Cost_{V2S} = \sum_{i,k,v,h} (C_{v,h}{}^{V2S} \times P_{i,k,v,h}^{V2S}) \tag{13}$$

$$Cost_{\deg} = C_{v}^{\deg} \times \sum_{i,h} R(P_{i,k,v,h}^{V2G} + P_{i,k,v,h}^{V2S}) \tag{14}$$

Where C^{v2g}, C^{v2s} and C^{deg} are the bidding prices of V2G, V2S and the degradation cost of EVs battery, respectively. p^{V2G} and p^{V2S} are power bidirectional transactions among EV-grid and EV-subway, respectively, as obtained from equations (15) and (16). R is the slope of segments in a linearized discharge curve. *i*, *k*, *v* and *h* are station, route, EVs, and hour indexes. p^{V2GC}

and p^{V2Gd} show charging and discharging power during V2G, respectively and p^{V2Sc} and p^{V2Sd} show charging and discharging power during V2S, respectively.

Equations (17) and (18) depict EVs' battery energy capacity for both states of V2G and V2S in form of static behavior, and also equations (19)-(24) demonstrate the discharging and charging limitations of the EV for bidirectional energy transfer. Due to the effects of traffic flow on EV energy consumption, the traction electrical power (P_{TE}^{s}) as the dynamic assignment of EV is imposed into total energy transaction at second as shown in (25)-(26).

- ***Static model***

$$P_{i,k,v,h}^{V2S} = P_{i,k,v,h}^{V2S^c} - P_{i,k,v,h}^{V2S^d} \tag{15}$$

$$P_{i,k,v,h}^{V2G} = P_{i,k,v,h}^{V2G^c} - P_{i,k,v,h}^{V2G^d} \tag{16}$$

$$E_{i,k,v,h}^{V2G} = E_{i,k,v,h-1}^{V2G} + P_{i,k,v,h}^{V2G^c} \times \eta_c - P_{i,k,v,h}^{V2G^d} \times \eta_d \tag{17}$$

$$E_{i,k,v,h}^{V2S} = E_{i,k,v,h-1}^{V2S} + P_{i,k,v,h}^{V2S^c} \times \eta_c - P_{i,k,v,h}^{V2S^d} \times \eta_d \tag{18}$$

$$E_{k,v,h} = \sum_i E_{i,k,v,h}^{V2G} + E_{i,k,v,h}^{V2S} \tag{19}$$

$$u_{i,k,v,h}^{c} + u_{i,k,v,h}^{d} = u_{i,k,v,h} \tag{20}$$

$$u_{i,k,v,h}^{c} P_v^{\min\_c} \le P_{i,k,v,h}^{V2S^c} \le u_{i,k,v,h}^{c} P_v^{\max\_c} \tag{21}$$

$$u_{i,k,v,h}^{d} P_v^{\min\_d} \le P_{i,k,v,h}^{V2S^d} \le u_{i,k,v,h}^{d} P_v^{\max\_d} \tag{22}$$

$$\begin{gathered} u_{i,k,v,h}^{c} P_v^{\min\_c} \le P_{i,k,v,h}^{V2G^c} \le u_{i,k,v,h}^{c} P_v^{\max\_c} \\ u_{i,k,v,h}^{d} P_v^{\min\_d} \le P_{i,k,v,h}^{V2G^d} \le u_{i,k,v,h}^{d} P_v^{\max\_d} \end{gathered} \tag{23}$$

$$E_v^{\min} \le E_{k,v,h} \le E_v^{\max} \tag{24}$$

- ***Dynamic model***

$$E_{k,v,h,s} = E_{k,v,h,s-1} - P_{TE}^{s} \tag{25}$$

$$\begin{aligned} E_{k,v,h,initial} = {} & E_{k,v,h-1,final} - \\ & \sum_i (P_{i,k,v,h}^{V2G^c} - P_{i,k,v,h}^{V2G^d} + P_{i,k,v,h}^{V2S^c} - P_{i,k,v,h}^{V2S^d}) \end{aligned} \tag{26}$$

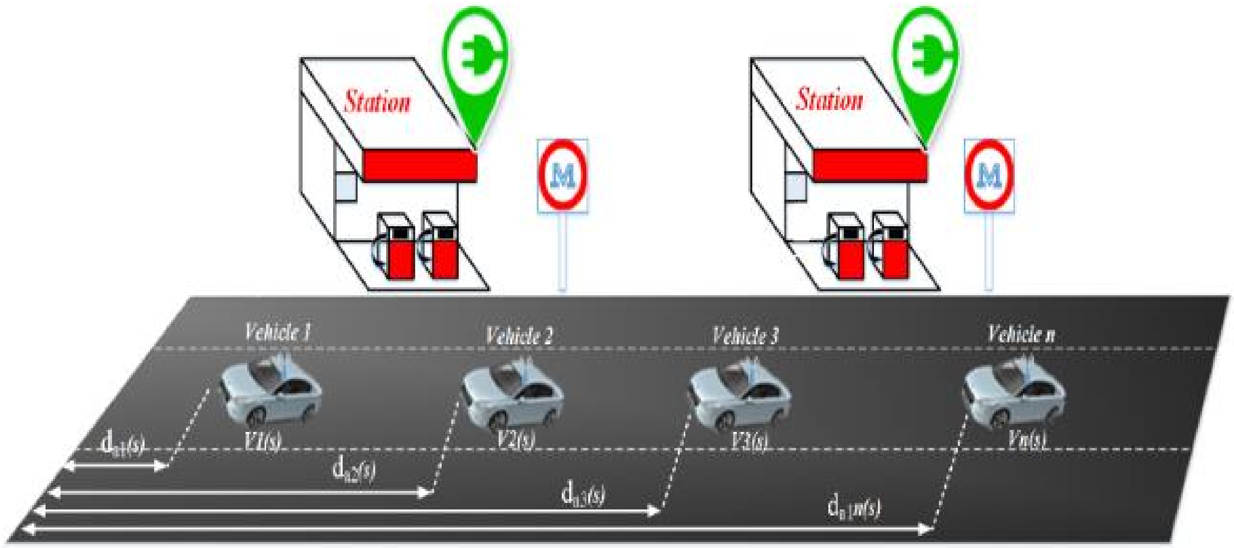


Fig. 3. The proposed dynamic transportation framework

Where η_c, η_d are efficiency of charging and discharging EV and u^c, u^d are binary variables of charge/discharge of the EVs' battery, respectively.

III. Directed Acyclic Graph-Based Cyber-Physical Security

As mentioned, this paper introduces a secure framework based on DAG to establish a dependable and secure decentralized environment in the proposed model. Given the data transactions among various components such as TSs and the power grid in the proposed model, it is imperative to employ a trusted framework with high accuracy to prevent unauthorized access [1]. The primary rationale for integrating blockchain into the proposed model stems from the necessity of EVs for real-time traffic flow information, which involves a significant volume of data exchange between electric vehicles. Consequently, data manipulation and modification can result in traffic congestion and subsequently increased energy consumption in TSs. Therefore, the primary objective is to ensure the security of energy and data exchanges between different systems such as EVs, subways, and networks, enabling the secure evaluation of the proposed RCTS model.

Hence, this section focuses on introducing a secure framework utilizing blockchain technology to secure data exchange. In essence, DAG is a modified blockchain method. Blockchain, a dependable and decentralized structure, consists of various nodes. These nodes are cryptographically joined through trustable ledgers in the environment.

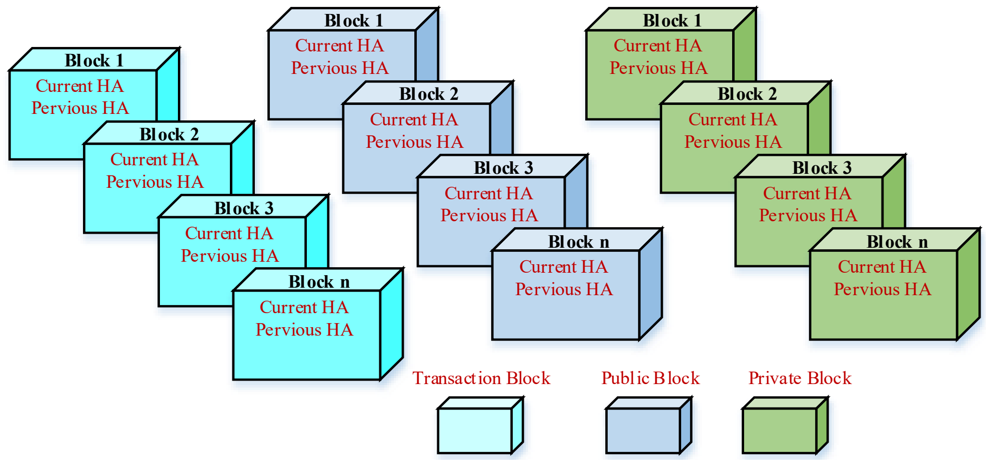


Fig. 4. Illustration of the DAG-based security structure

In the blockchain, each node will make an energy and data block which is secured and encrypted by a peculiar hash address to restrict unauthorized access. Secured agents are broadcasted to the other nodes that are advanced through a unique key as a recognition and verification tool. Generally, in the public structure of the blockchain approach, the information of data blocks is available for each node that can be accessed via a public key. Encryption of data and energy blocks in the blockchain procedure is one of the dilemmas related to this method, which reduces the accuracy of calculating hash addresses in complex systems with a large number of connections. In addition, unauthorized cyber access due to the cyclical nature of blocks has led to accretion in cyber menaces. To conquer the mentioned problems, in this paper, a modified blockchain method-based DAG approach is proposed for energy and data transactions within the proposed RCTS. In the DAG approach, Data, which includes information from EVs, subways, and the grid, is divided into private, public, and transactional categories by nodes. The private data is owned by the nodes of an agent which will be distributed by the private blockchain. This data will not be obtained by other nodes of the later agent. In the public blockchain, all data that is publicly accessible, created by nodes, is shared among agents. The data transaction from the nodes of an agent to other nodes of later agents can be broadcasted by the transaction blockchain. This data is only obvious for the receiver and sender nodes. The data blocks within the acyclic structure are transferred to the nodes in the proposed framework. To verify the authenticity of data, each node will access blocks containing both current and previous data, along with their respective hash addresses. The nodes make the current hash address and transfer it to the other agents as the previous hash address for decoding the data block. This process resumes for all blockchain layers. The generated hash addresses are different for three layers of the blockchain (private, public, and transaction), which can increase the security level of data in all sections. The structure of blockchain-based DAG is shown in Fig.4. The decentralized and acyclic structure of DAG has increased the security of data transactions among TSs and the power grid. However, in the transaction blockchain layer, the dependency of hash addresses among data blocks has increased the risk of cyber threats and limited the security of the smart city. An attacker might access information or inject malicious data into the transaction. To overcome such a problem, this paper suggested a source-based cryptographic approach wherein considered the unique hash addresses for each data block. In fact, the data blocks are transmitted to the other agents with various hash addresses which are haphazardly chosen. Also, a hash index is allocated to each data block and transmitted to the recipient protected versus the data attackers.

IV. COPULA FUNCTION BASED UNCERTAINTY MODEL WITHIN SMART CITY

In the proposed model, EVs are evaluated simultaneously in both static and dynamic assignments. Concerning the random behavior of EVs in the traffic flow (dynamic state) and charging stations (static state), modeling the uncertain parameters enables the real evaluation and also accurate energy management of EVs in TS. In the proposed model, the charging demand of EVs and traffic density are uncertain variables influenced by different parameters such as charging current/voltage, battery capacities, number of EVs, the charging duration, EV speed. Indeed, developing the uncertainty framework is necessary to model the complex, and uncertain behaviors of parameters. This section introduces the copula function to represent and model the unanticipated uncertainties parameters of EVs such as the charging demand of EVs and traffic density.

The copula function was first introduced by Sklar in 1959. A copula function is a powerful tool for analyzing the dependencies between random variables and obtaining their joint probability distribution function. Flexibility and modularity are the merits of the copula, that is, each marginal distributions with different variables follow. We can derive functions with types of distributions and integrate them. In fact, functions that do not class to the same distribution can be conjugate with each other. Also, this method doesn't need normality in joint or marginal distributions and permits the construction of the common distribution of different variables with various marginal distributions [35]. Hence, we use the advantage of the copula in flexibly modeling the dependency structure of TSs. The copula function is a function that associates the joint probability distribution with the joint cumulative distribution functions of each of the variables (the charging demand of EVs and traffic density). Assume that the cumulative distribution functions of variables x_1 (the charging demand of EVs) and x_2 (traffic density) are $f_1(x_1)$ and $f_2(x_2)$, respectively. Also, their cumulative distribution function is $F(x_1, x_2)$. Accordingly, according to the Sklar theorem, cumulative distribution functions can be joined by copula function C as defined:

$$F(x_1, x_2) = C(f_1(x_1), f_2(x_2)) \tag{27}$$

Random variable $U=F(x)$ is a uniform distribution function in the range [0, 1]. According to equation (27), it is assumed that $U_1= F_1(x_1)$ and $U_2= F_2(x_2)$, and also their cumulative distribution function can be calculated with equation (28). Therefore, the copula function can be expressed as the following equation (29) [35]:

$$\begin{aligned} &for \quad u \in [0,1]: P(U \le u) = P(F(x) \le u) = P(x \le F^{-1}(u)) \\ &= F(F^{-1}(u)) = u \end{aligned} \tag{28}$$

$$F_{1,2} = P(U_1 \le u_1, U_2 \le u_2) = (F_1^{-1}(u_1), F_2^{-1}(u_2)) = C(u_1, u_2) \tag{29}$$

As is clear from the above equations, the cumulative distribution function of each of the random variables (as the charging demand of EVs and traffic density) is the input of copula functions. The cumulative distribution function can be easily calculated if the distribution function of each variable is known, and if the type of distribution is not known, it can be simply determined using experimental relations. As mentioned earlier, one of the important advantages of copula functions is the correct modeling of dependencies between random variables. This method is able to accurately model the linear and nonlinear dependencies of variables (as the charging demand of EVs and traffic density) that dependence plays an important role in them. There are different types of copula functions, each of which has unique properties. One of the major challenges in modeling uncertainty using copula is the proper selection of the type of copula. Paying attention to this issue and considering the most appropriate copula will lead to more accurate modeling. In general, copula functions are divided into two categories: elliptical copula and archimedean copula; elliptical copula includes Gaussian and T, and archimedean copula includes Clayton, Frank, and Gamble [31]. The selection process of the copula function is as:

Step 1 **-** Select several conventional copula functions.

Step 2- Calculate the parameters of the selected copula functions, using the maximum likelihood estimation method and according to the input data (the charging demand of EVs and traffic density).

Step 3- Optimal selection of one of these functions based on Spearman correlation coefficient of primary data with data generated by each function and Euclidean distance criterion of copula functions with empirical copula function.

Fig. 5 illustrates the flowchart of the random modeling algorithm of copula functions.

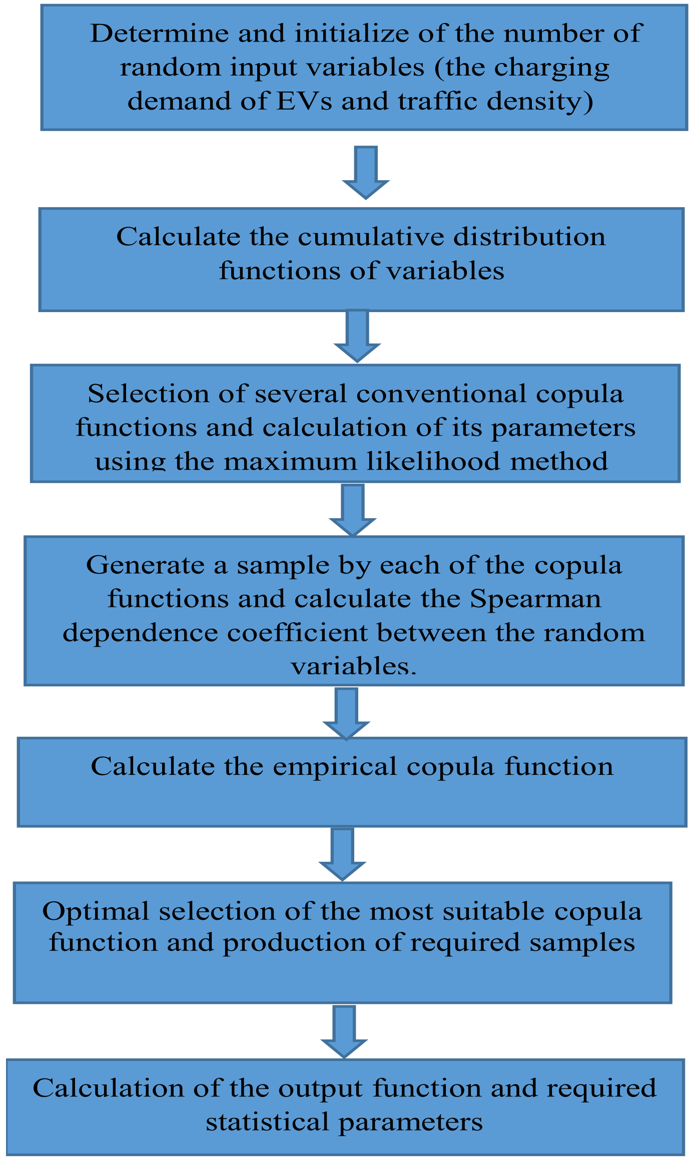


Fig. 5. Performance process of the copula function-based algorithm

V. ASSESSMENT OF THE PROPOSED MODEL

A. *The proposed co-dynamic-static energy model analysis*

This section is devoted to the execution evaluation of the presented RCTS-based smart city model as seen in Fig.1. The proposed model is a mixed integer problem that has been implemented in GAMS software by the CPLEX solver and also MATLAB software on PC with 32 GB of RAM. As mentioned, the dynamic-static model of energy systems based on the RCTS is provided in the smart city environment. The parameters, the technical and specialized requirements of EVs, subway stations, and the power grid are adapted from [3]. Table 3 displays parameters such as the number of EVs, access time, charge/discharge limitations, and available arrival time of the EVs. We have tried to use real datasets, detailed data such as the EVs' battery energy capacity, speed, traffic density [39], substation energy profiles and etc. have been selected from Madrid's details [8]. Hence, we hold the proximity of the results and analysis to the experimental results. The parameters and coefficients of vehicle power in traffic flow as described in equation (7) are derived from [22].

TABLE 3
EVS FLEET CHARACTERISTICS

Fleet No.	EVs No.	Access Time	Capacity (kWh)		Charge and 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

Assuming that there are 6 electric vehicles (EVs) with access to multiple charging stations via two lanes in the static assignment. The charging stations include subway station parking and EV station parking within a 24-hour daily horizon. For accurate modeling, the dynamic assignment of EVs when they are in traffic flow is assessed. The consumption power in the current traffic flow is based on EVs' speed. For instance, the speed discrepancies of the first EV at the hour t = 4 (1 to 3600 seconds) can be noticed in Fig. 6.

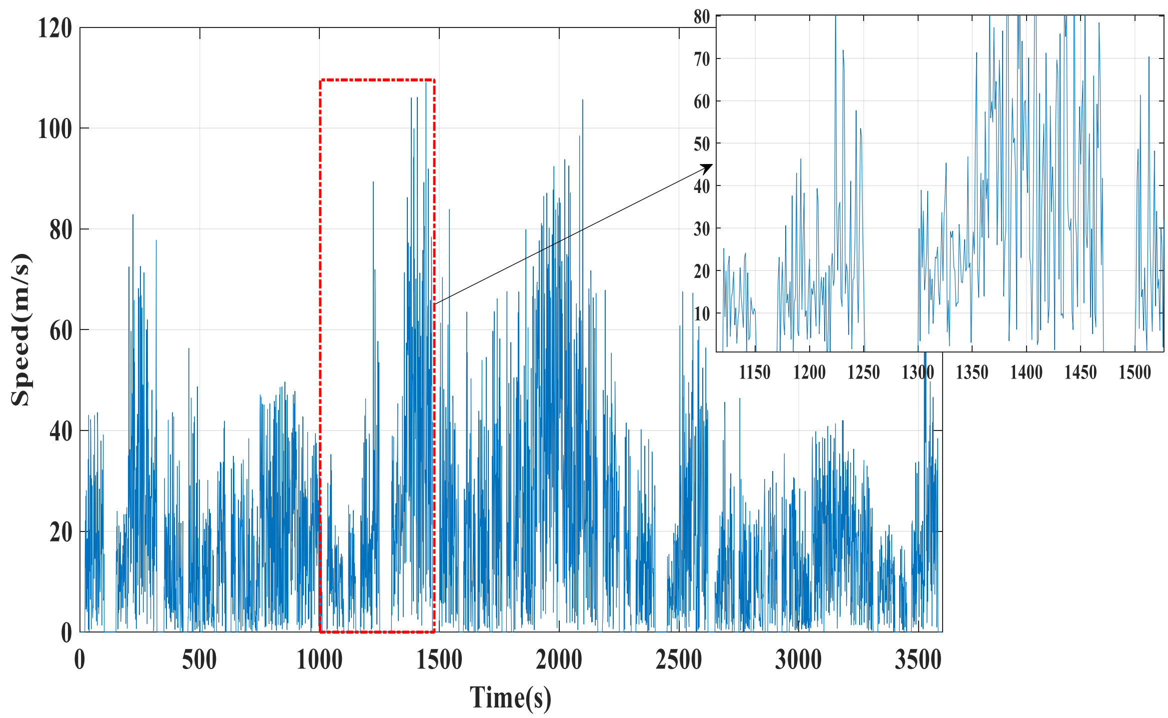


Fig. 6. The EV' speed model based on the traffic on road at *t=4* (1 to 3600 second)

The presented model based on RCTS structure has enabled comprehensive behavioral modeling of TSs. In this model, it is feasible to energy consumption management in a statically-dynamically behavior within charging stations accompanying traffic flow on road. For this regard, first, the status of TSs in the proposed model as the energy real management system of EV and the energy management system of the subway are examined. According to Fig. 7, the RCTS model within the energy management systems of the EVs and subway are shown on the right and left of Fig, respectively. This case is specifically assessed for the second EV (EV2) and at hours t=2. EV2 can engage in energy transactions with the grid and the subway through two parking lot connections, V2G and V2S. Generally, EV2 charges and discharges power in proportions of 53.85% and 46.15%, respectively. Of the total charged energy (53.85%), 14.56% is sourced from the power grid, while 85.46% is obtained from the subway station. This facilitation of energy exchange between EV2 and the subway station has led to a significant portion of energy consumption being supplied by regenerative braking energy. The discharged energy from EV2 originates from the grid, the subway station, and traffic flow. As depicted in the figure, the majority of EV discharge energy (80.70%) results from the energy consumption of EVs within traffic on the road. Therefore, it can be concluded that modeling vehicles in traffic flow can significantly impact the energy management program. Additionally, the remaining discharged energy is allocated to both the subway station and the power grid. From the perspective of the subway energy management system, 99.60% of the total electricity consumption of the subway is attributed to subway load, while the remaining portion is related to EV charging energy. Essentially, energy sources for supplying the subway load include regenerative braking energy, the grid, and EV discharging. Of the total subway load consumption (99.60%), 63.07% is provided by the grid, while 34.87% and 2.08% are supplied by subway regenerative braking energy and EV discharging energy, respectively. With this rationale, the proposed co-dynamic-static model-based RCTS within the smart city environment is provided in Fig.7

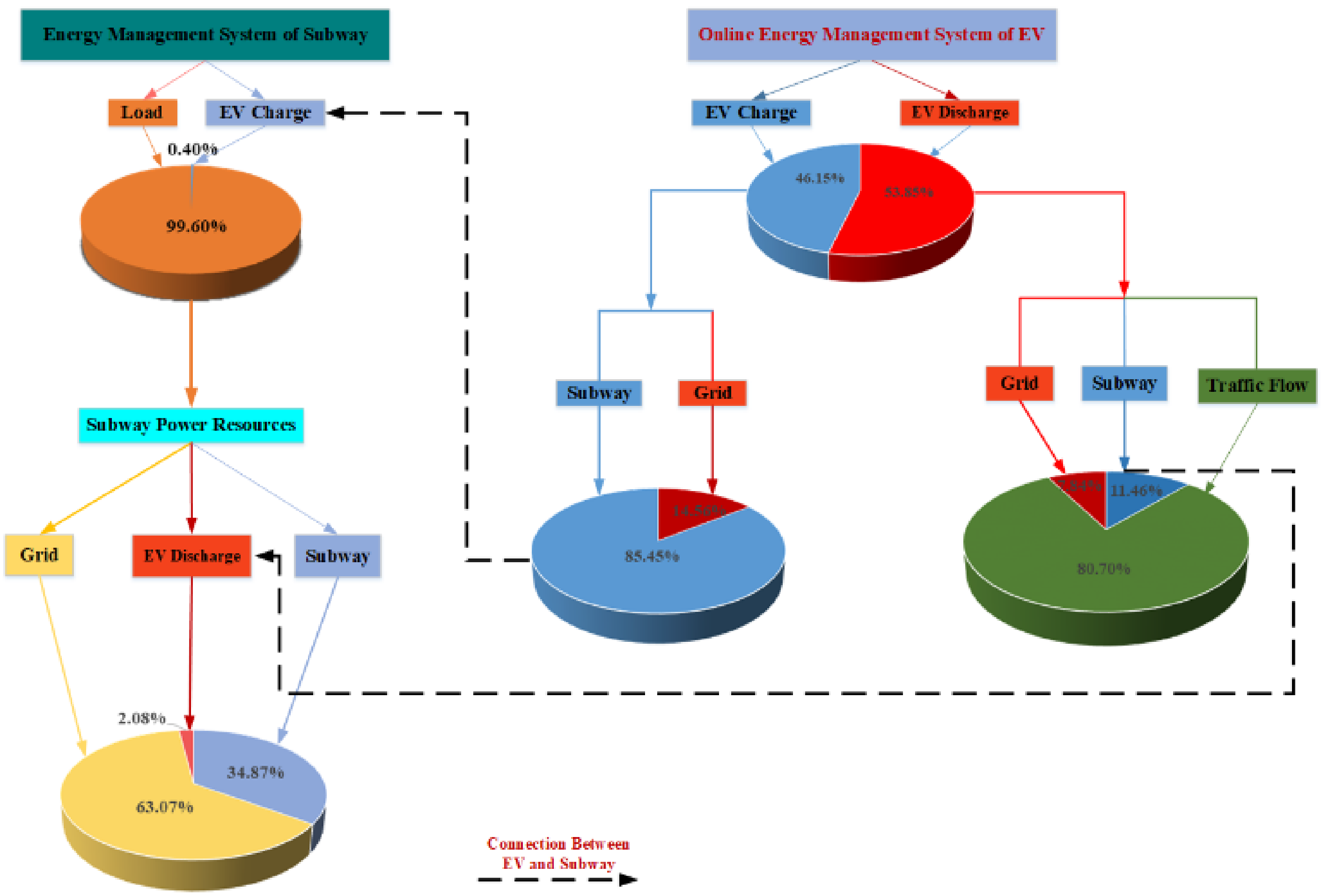
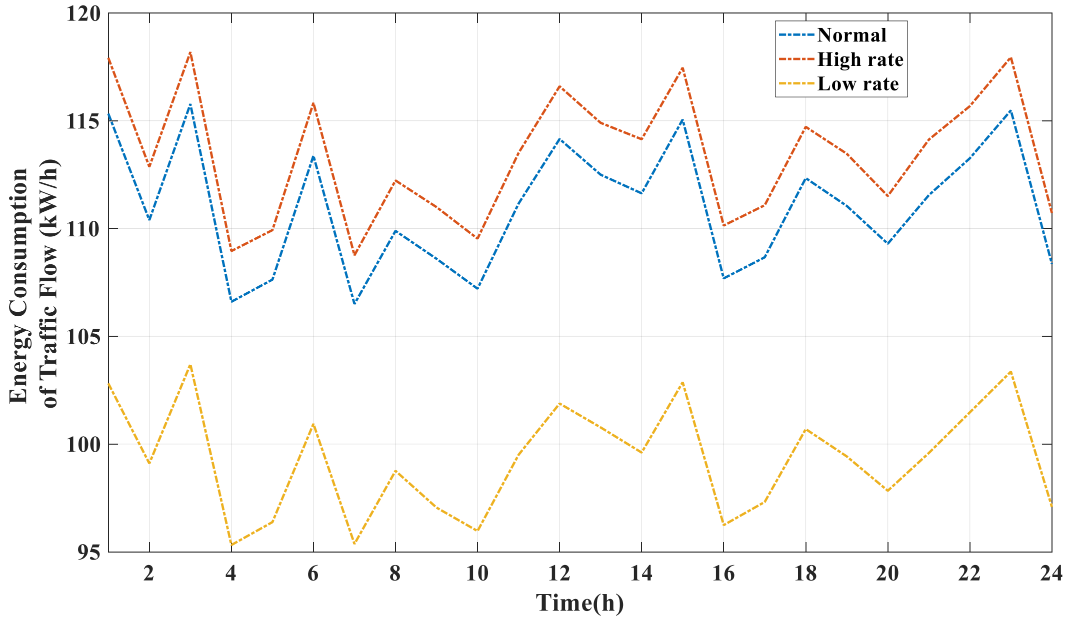


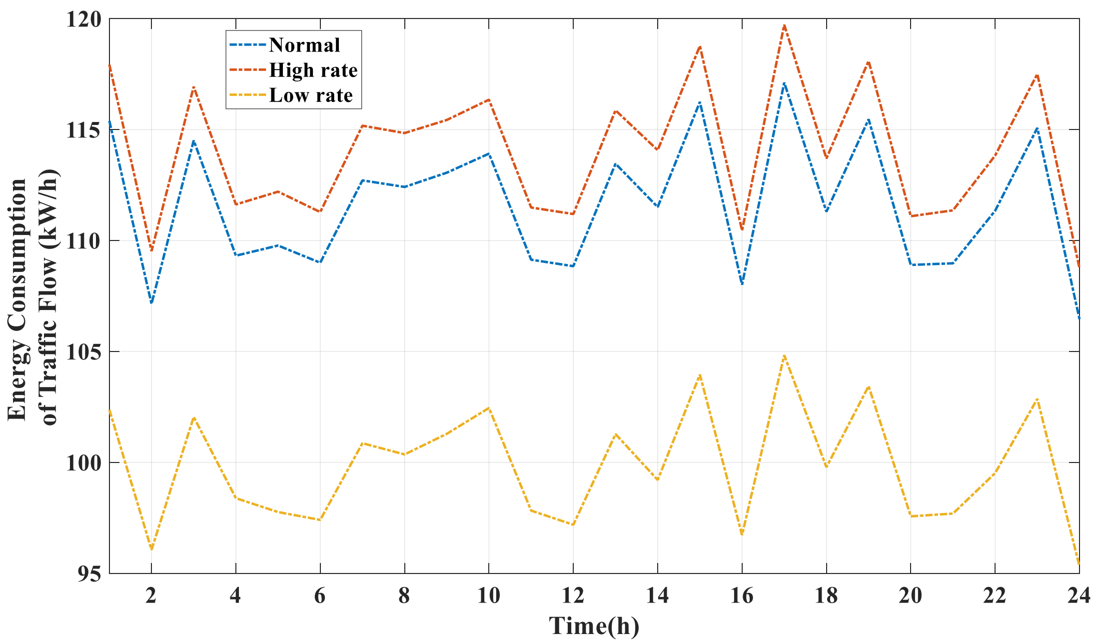
Fig. 7. The performance of the co-dynamic-static energy model within RCTS

Here, the performance analysis of the proposed model is investigated to various extents, including different traffic flow rates due to changes in speed. Fig. 8 shows the amount of energy consumption of EV1-EV6 in traffic flow, respectively. EVs are evaluated in three cases arising from different traffic rates. The first case reveals normal traffic flow, the second case shows low-rate traffic, and the last case shows high-rate traffic.



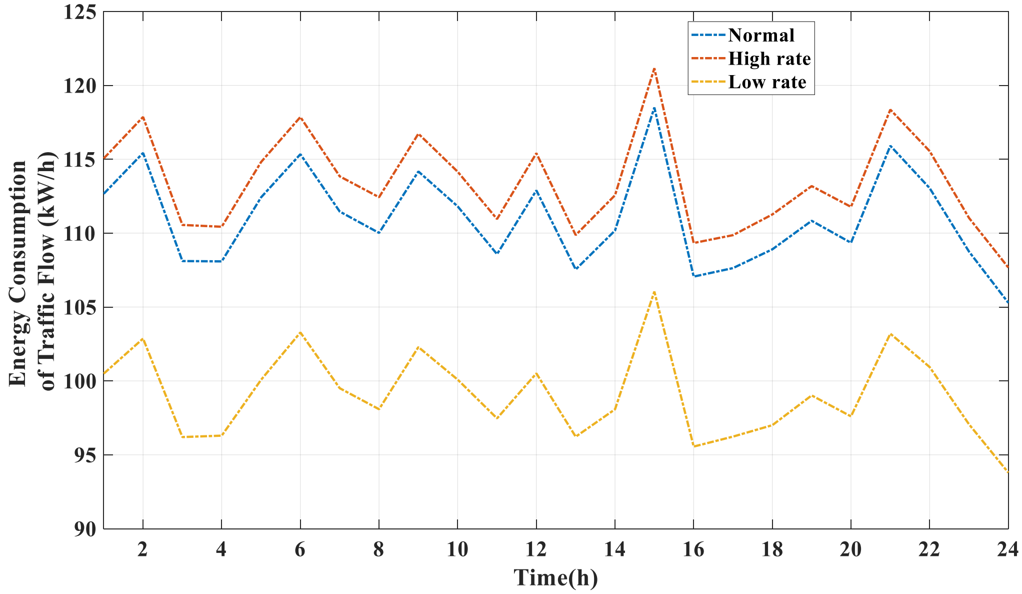
120
115
110
105
100
95
Energy Consumption
of Traffic Flow (kW/h)
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)
Normal
High rate
Low rate

a:EV(1)

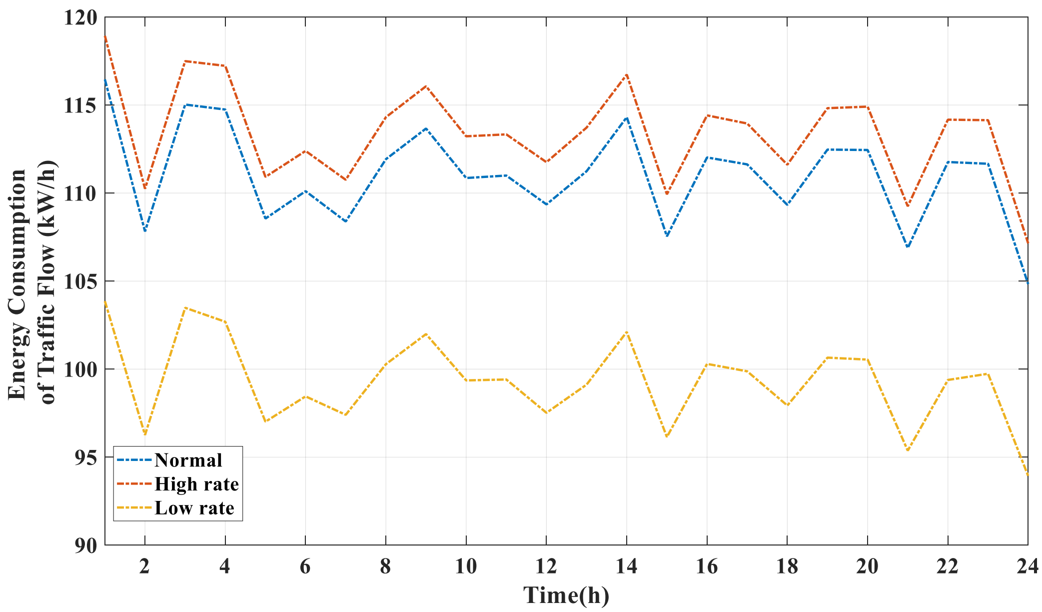


120
115
110
105
100
95
Energy Consumption
of Traffic Flow (kW/h)
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)
Normal
High rate
Low rate

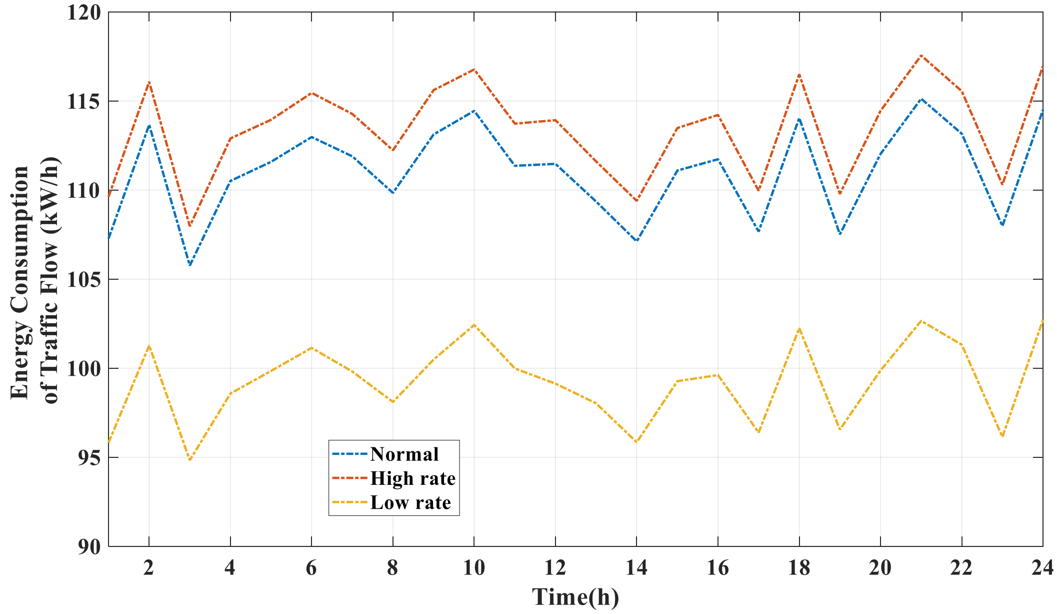
b:EV(2)


Normal
High rate
Low rate
Energy Consumption of Traffic Flow (kW/h)
Time(h)

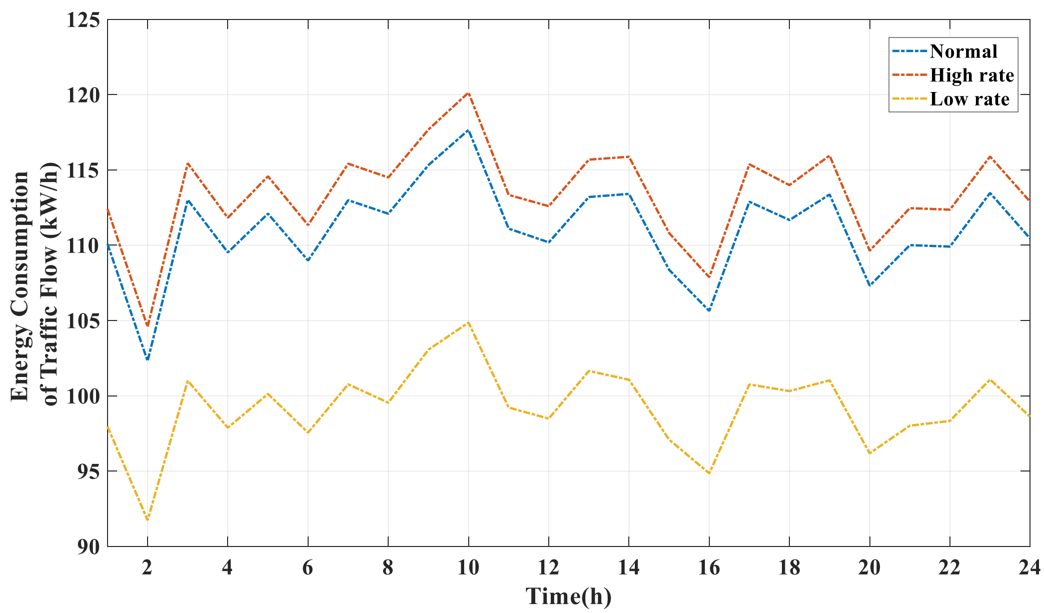
c:EV(3)


Normal
High rate
Low rate
Energy Consumption of Traffic Flow (kW/h)
Time(h)

d:EV(4)

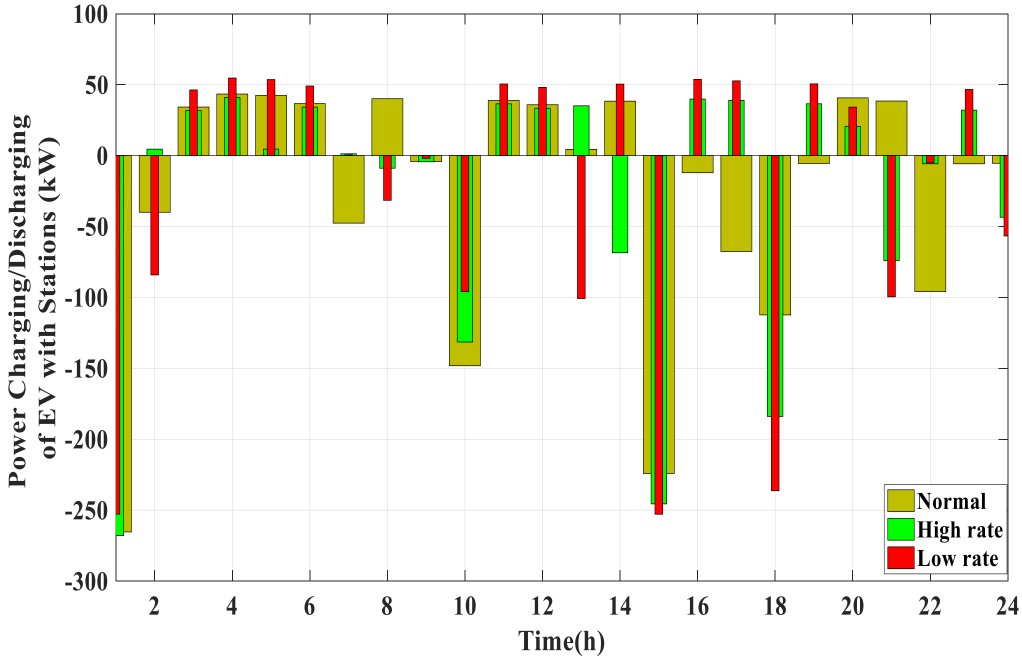


e: EV(5)



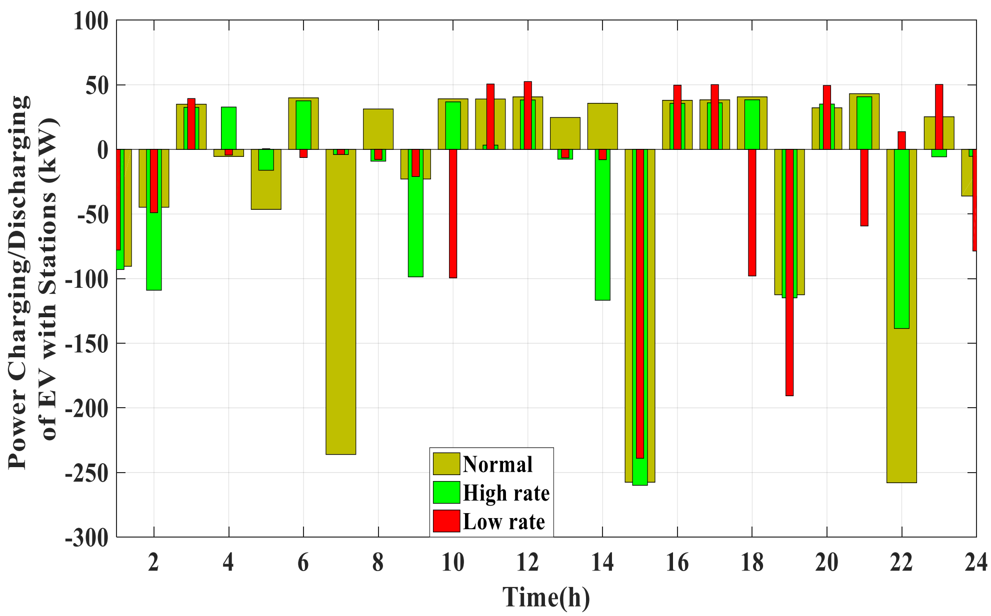
f:EV(6)

Fig. 8. The energy consumption of EVs on traffic flow for the different traffic rates: a)EV(1):f)EV(6)



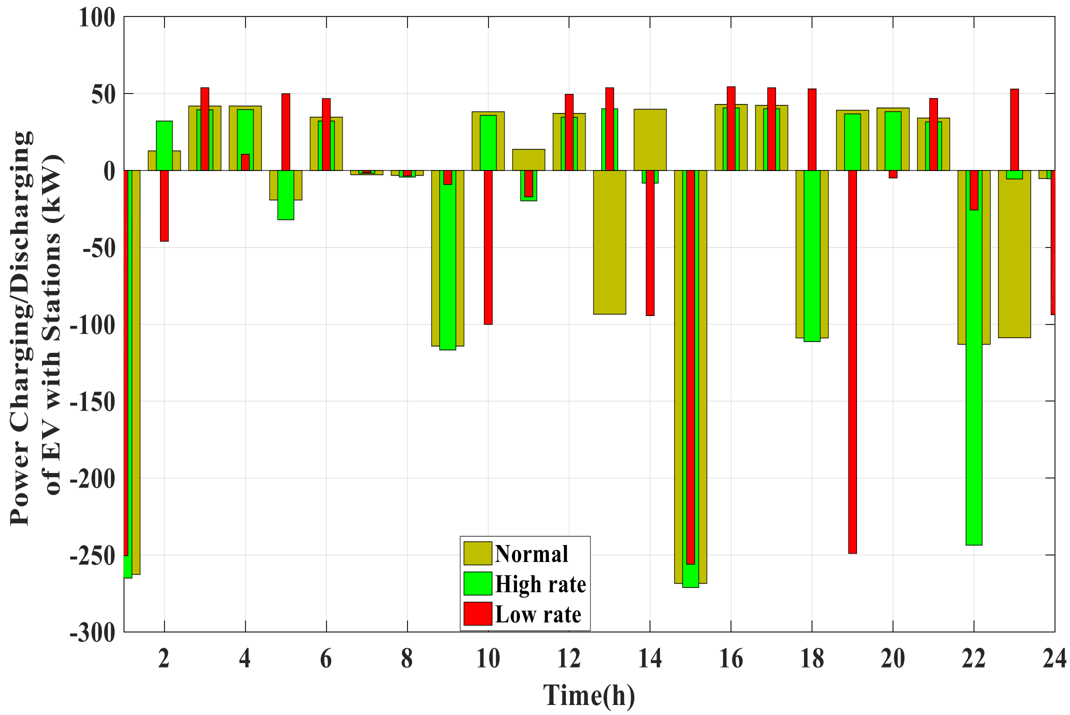
Power Charging/Discharging
of EV with Stations (kW)
Time(h)
Normal
High rate
Low rate
100
50
0
-50
-100
-150
-200
-250
-300
2
4
6
8
10
12
14
16
18
20
22
24

a:EV(1)

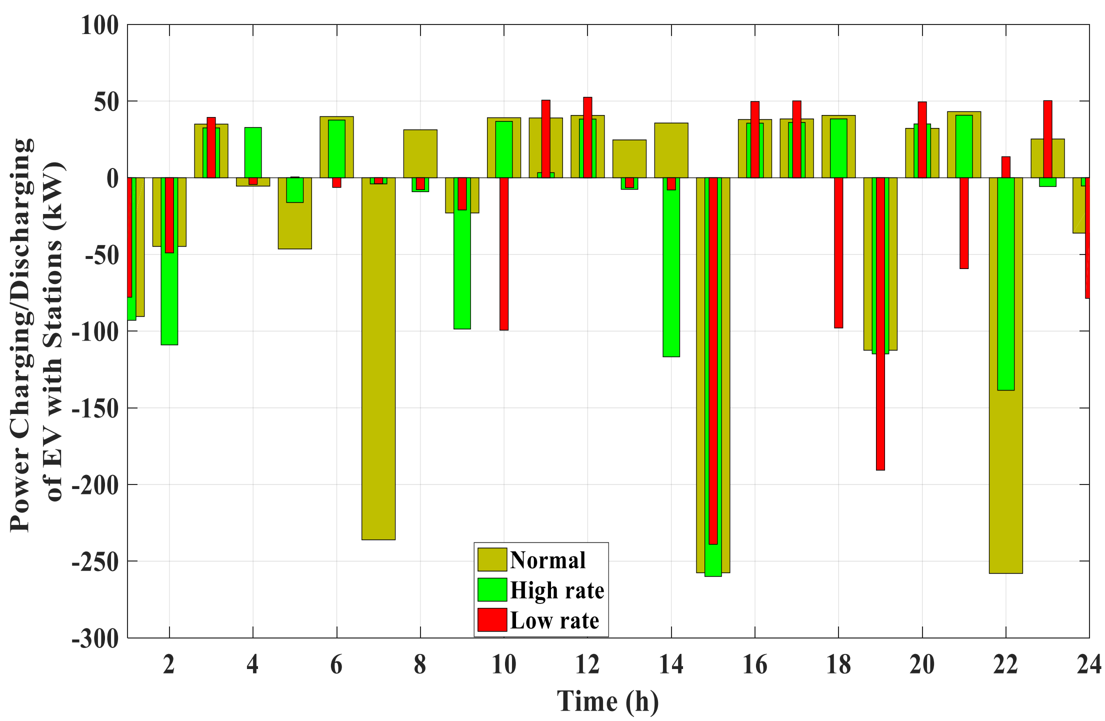


Power Charging/Discharging
of EV with Stations (kW)
Time(h)
Normal
High rate
Low rate
100
50
0
-50
-100
-150
-200
-250
-300
2
4
6
8
10
12
14
16
18
20
22
24

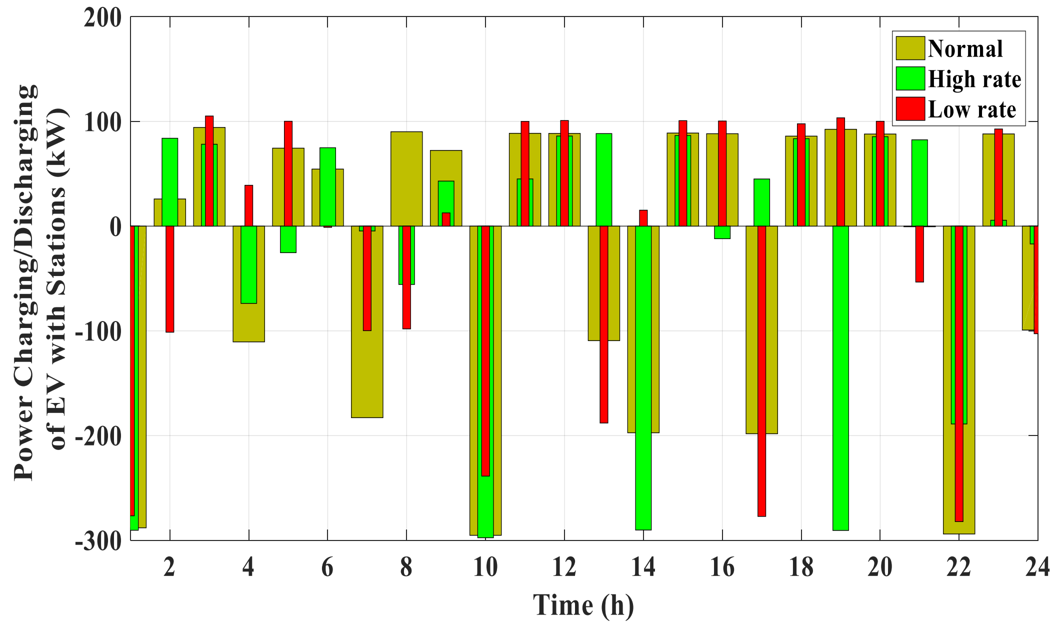
b:EV(2)


100
50
0
-50
-100
-150
-200
-250
-300
Power Charging/Discharging
of EV with Stations (kW)
2 4 6 8 10 12 14 16 18 20 22 24
Time(h)
Normal
High rate
Low rate

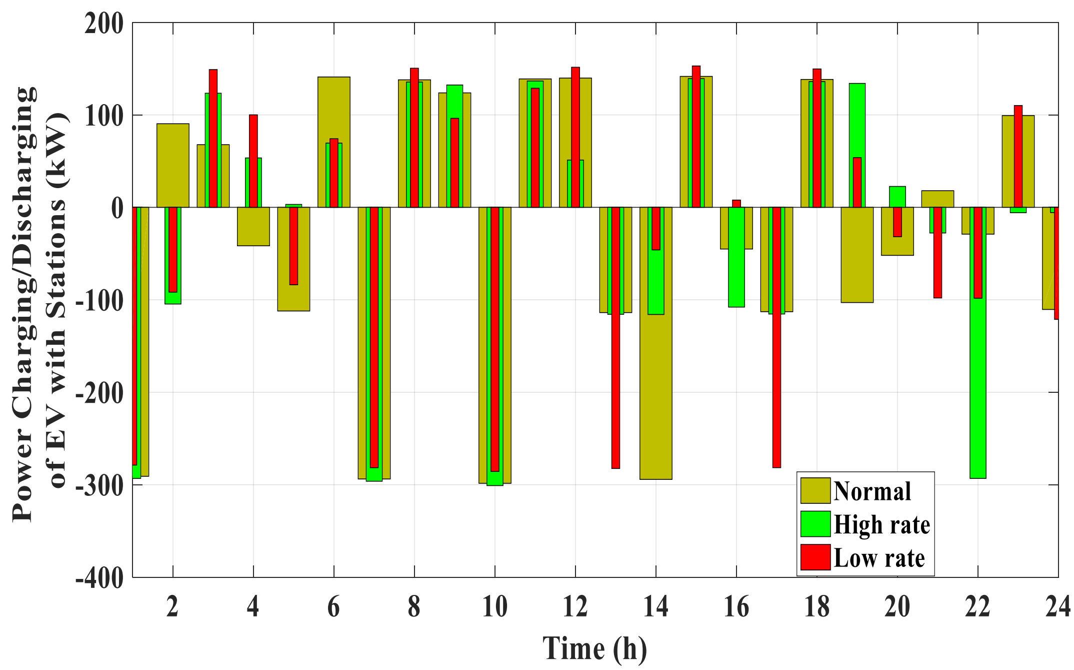
c:EV(3)


100
50
0
-50
-100
-150
-200
-250
-300
Power Charging/Discharging
of EV with Stations (kW)
2 4 6 8 10 12 14 16 18 20 22 24
Time (h)
Normal
High rate
Low rate

d:EV(4)



e:EV(5)



f:EV(6)

Fig. 9. The EVs performance based on static condition under different traffic rates: a)EV(1): f)EV(6)

According to the figure, the energy consumption amount of EV1 increases by 3% with the increase in the traffic rate (high rate), and also this amount of energy decreases by 10% at the low rate compared to the normal condition. As it is clear, the traffic flow rate has a direct effect on energy consumption of EVs as well as the energy management system. These results prove that EVs perform such reactions due to such data inspired by real data. Considering the occurrence of such behavior in real conditions, such results can be considered a relatively real output. Also, having knowledge of the energy consumption of

EVs on an hourly basis allows for a more thorough analysis of the vehicles in static assignment. Consequently, this facilitates more precise planning and operation of the upstream network. Furthermore, the effect of traffic flow rates on the performance of EVs' energy interaction (charging/discharging) with charging parking lots, which is introduced as a static assignment is investigated. Fig. 9 illustrates the charging and discharging patterns of EV1 to EV6 in conjunction with substations across the three specified scenarios. According to the figure, EV1 exhibits a 16% variation in charging and discharging power (at 10 o'clock.) under high traffic conditions and a 33% variation in charging and discharging amount during low traffic compared to normal conditions. This performance mirrors the behavior observed in real energy management systems of stations, reflecting the dynamics captured by actual datasets. In essence, based on the figure, it can be inferred that the variation in traffic rate (low, normal, and high) not only impacts the quantity of energy consumed by EVs per hour but also alters the mode or pattern of energy consumption (charging) or production (discharging) of EVs. Therefore, a shift in the EV's planning due to alterations in the consumption pattern results in adjustments to the planning and operation of the upstream network. For instance, as illustrated in Fig. 9, EV(4) is in charging mode at 6 p.m. under normal conditions, whereas the pattern shifts to both charging and discharging modes, respectively, with the increase and decrease of the traffic rate. EV(3) remains in charging mode at 2 a.m. under normal and high traffic rates, with charging powers of 20 and 45 kW, respectively. However, with a decrease in the traffic rate, the mode shifts to discharging, with a discharge power of 48 kW. Exactly, for precise planning and operation, it is essential to have accurate information about the conditions of the cars and the traffic rate. This enables better decision-making and optimization of resources in the transportation system.

The examination of the newly proposed model for accurately assessing the performance of electric vehicles (EVs) within the co-dynamic-static framework, along with the obtained results, underscores the necessity of simultaneously modeling EVs across various traffic rates. Moreover, both economic and technical planning necessitates such a model for transportation systems. In summary, the proposed RCTS model entails a comprehensive analysis of transportation systems' performance within the energy management framework. As mentioned earlier, EVs can charge/discharge themselves based on two forms of parking lots: 1) Connection V2G 2) Connection V2S. Traditionally, EVs can only connect to the grid through V2G strategy, while the RCTS framework enables EVs to utilize the hybrid V2G&V2S strategies resulting in the EVs’ performance enhancement for traffic conditions. Given this fact, Table 4 shows the comparative results related to transportation energy costs (¢) in different traffic rates based on two scenarios: 1) RCTS model and 2) without connection V2S. Based on the table, it is evident that as the traffic flow increased, the energy costs of electric EVs also increased for both scenarios 1 and 2. In the RCTS model (scenario 1), EVs have the potential to reduce energy costs by up to 6.21% on average compared to scenario

2 across normal, low, and high traffic rates. Additionally, without the V2S connection, the subway system witnessed an average increase of 60.33% in energy costs, indicating that the subway's performance could improve under the RCTS model. Therefore, it is a must to analyze the comprehensive behavioral modeling of TSs that takes into account co-dynamic-static conditions for accurate planning of economic and technical requirements.

TABLE 4
THE ENERGY COST OF TRANSPORTATION SYSTEMS UNDER DIFFERENT RATES OF TRAFFIC

	RCTS			Without Connection V2S		
Transportation	**Normal condition**	**High rate condition**	**Low rate condition**	**Normal condition**	**High rate condition**	**Low rate condition**
EV energy Cost/Benefit (¢)	604662.5978	634466.4255	499354.0218	7.0425×10^{5}	6.6537×10^{5}	5.0430×10^{5}
Subway energy Cost/Benefit (¢)	3.66863×10^{15}	3.64405×10^{15}	3.75341×10^{15}	4.282×10^{15}	2.309×10^{16}	2.309×10^{16}

B. Evolution of the DAG approach for data security of the co-dynamic-static model of the RCTS

As described, the private, transactional, and public blockchain are utilized for data transactions within the components of each system, inter-system data transactions, and distribution of public data, respectively. Table 5 represents the security evaluation-based blockchain of the TSs within the smart city at t=4. To disseminate public information for each system, the public blockchain is employed across all systems. According to the Table, Energy price, considered as public data, is conveyed using the public blockchain. Conversely, the consumed energy of EV4 and station4 load are treated as private information within the TSs, transmitted to a private blockchain through a private data block, secured with a hash address.

Additionally, the transaction blockchain facilitates data transactions among EVs and charging stations, typically around 5kW. Similarly, the aforementioned findings at t=13 are depicted in Table 6. Given that TSs enable bidirectional energy exchange, they are recognized as distributed sources. Hence, the utilization of a blockchain-based DAG security structure, which necessitates a distributed framework, could be compatible.

TABLE 5

THE DAG APPROACH-BASED SECURITY ASSESSMENT FOR PROPOSED RCTS AT T=4

Data Blocks	**Time=4**		
	Block information		Previous HA
Private	Consumed energy of EV(4) (kW)	Station load (4) (kW)	Current HA

	116	5.2	
Public	Price (¢/kWh)		Previous HA
	7.5		Current HA
Transaction	EV to Stations(kW)		Previous HA
	5.467847299		Current HA

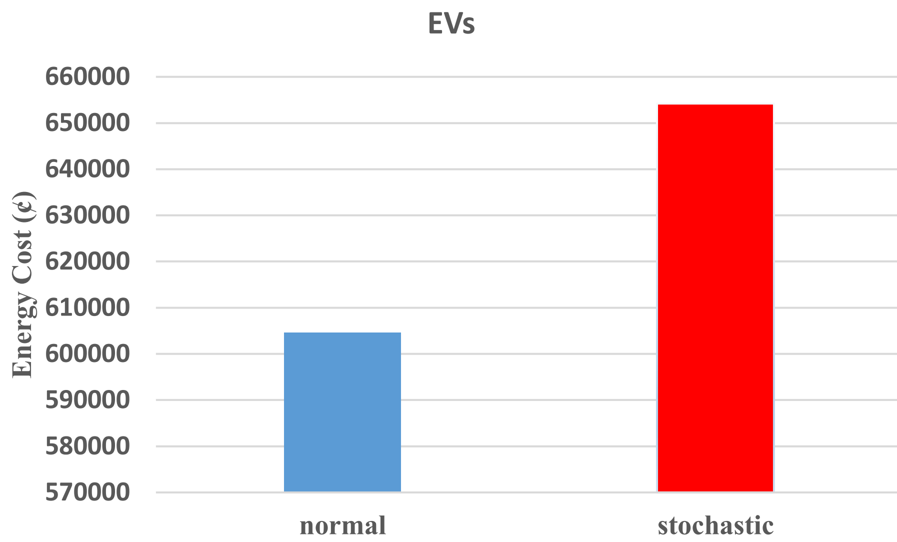
TABLE 6

THE DAG APPROACH BASED SECURITY ASSESSMENT FOR PROPOSED RCTS AT T=13

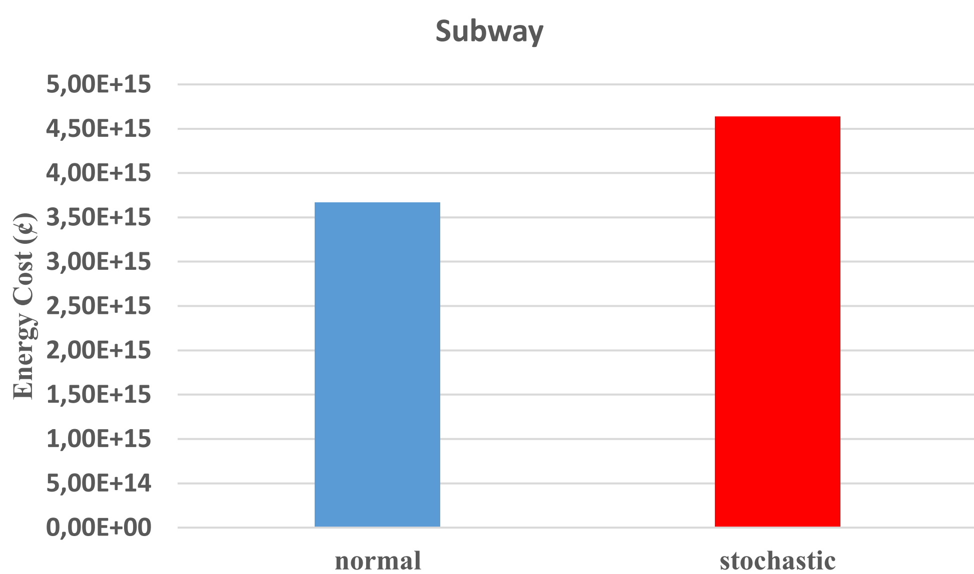
Data Blocks	**Time=13**		
	Block information		Previous HA
Private	Consumed energy of EV(3) (kW)	Station load (3) (kW)	Current HA
	107	702.00	
Public	Price (¢/kWh)		Previous HA
	10		Current HA
Transaction	EV to Stations(kW)		Previous HA
	-93.4730906		Current HA

C. Examination of the copula approach based the uncertainty

Uncertainty significantly influences the output and results of problems, posing numerous challenges to the operation of the RCTS in smart city management, particularly when dealing with uncertainty agents such as traffic flow. Therefore, modeling this uncertain nature becomes imperative. Fig. 10 compares the stochastic and deterministic analyses of the proposed co-dynamic-static model. It is evident from the figure that uncertainty analysis alters the total optimal cost of the smart city. As elucidated, integrating uncertainty into energy management ensures precise energy scheduling for the smart city. Upon reviewing Fig. 10, it can be inferred that fluctuations in EVs' energy costs are approximately 6.04662×105 and 6.5421×105 for normal and stochastic conditions, respectively. Similarly, for the subway system, these values are approximately 3.66863×1015 and 4.637×1015 for normal and stochastic conditions, respectively. In summary, modeling the stochastic co-dynamic-static energy structure enhances the optimality and reliability of energy management within real transportation systems.



a



b

Fig. 10. Total cost under the normal and uncertainty models: a) EVs, b) subway system

VI. CONCLUSION

This paper provided a novel traffic flow density based co-dynamic-static model based on RCTS. This proposed model has been presented to seek targeted interoperability among mobile energy resources. The major aim of this model is behavioral modeling of EVs that is devoted to statistical dynamicity to an accurate evaluation, simultaneously. The energy administration model in the traffic flow system is committed to enabling the dynamic assignment considering the power consumption involved by the moving density of vehicles. As mentioned, the traffic flow model as the dynamic assignment is dependent on the traffic flow density parameter, and this parameter is based on the speed variation of EVs. It also leads to changes in electrical power which is a leading factor in EV's performance in the static assignment. The static behavior signifies the impact of traffic flow on the performance of the EV's energy exchange with parking stations is known as a static assignment. As the TSs are known as distributed sources, so, the use of a distributed security structure can be compatible. In this regard, the directed acyclic graph (DAG)-based decentralized cyber security for RCTS-aided smart city ecosystem is proposed. Data transactions in the mobile energy resources are secured through the blockchain blocks against cyber-attack. Furthermore, the stochastic structure-based copula function is provided to construct precise management surroundings within the smart city. The analysis of the proposed novel model for the precise evaluation of EVs performance in a co-dynamic-static model and the presented results confirm the need to model EVs in both dynamic and static assignments, simultaneously.

<u>Data would be provided on the request.</u>

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