Complexity Assessment with K-Weighted Entropy for Cloud-Edge-Vehicle System

Yanjun Shi*
School of Mechanical Engineering
Dalian University of Technology
Dalian, China
syj@ieee.org

Jiajian Li
School of Mechanical Engineering
Dalian University of Technology
Dalian, China
lijiajian@mail.dlut.edu.cn

Lingling Lv
School of Mechanical Engineering
Dalian University of Technology
Dalian, China
lvlingling@mail.dlut.edu.cn

2021 IEEE International Conference on Smart Internet of Things (SmartIoT) | 978-1-6654-4511-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/SmartIoT52359.2021.00054

***Abstract*—With the continuous integration of Internet-of-things (IoT) devices in smart cities, smart homes, and intelligent industries, complexity assessment considering the interaction between cyber-physical networks has practical value to ensure the stable operation for edge computing of Intelligent Transportation System (ITS). However, there are few effective methods for assessing the complexity of edge-computing networks and services. Enlightened by the potential of complex networks, a Cloud-Edge-Vehicle (CEV) hierarchical paradigm was proposed for the collaborative Vehicle-road Edge Computing System (VECS) and mapped into cyber-physical networks. Furthermore, an improved Complexity Evaluation Method based on *K*-weighted Entropy (CEM-KE) was proposed to quantitatively assess the complexity of the architectural design to the VECS. Experimental results on various topological structures demonstrated a comprehensive assessment of complexity with the qualitative and quantitative analysis of *K*-weighted entropy and showed the feasibility of the proposed method. In the real-world application, the optimization design of VECS can be taken as the process of reducing entropy, and CEM-KE can provide design guidance to reduce the structural redundancy in multilayer networks.**

Keywords*—*structural complexity, complex network, entropy, cloud-edge computing

I. Introduction

The expansion of the Internet of Things (IoT) presents ubiquitous connections in the size, scope and complexity that almost all the devices and appliances connect to the network and span multiple levels of the Industrial organizations[1]. The increasing diversity of IoT devices and the complexity of IoT systems have made assessing the rationality of configuration design extremely difficult in such a multitude of IoT elements[2]. With the evolution of intelligent transportation, the collaborative Cloud-Edge-Vehicle Computing System (CEVCS) in the future will be a complex cyber-physical system[3]. The incorporation of the Intelligent Transportation System (ITS) in the context of smart cities significantly increases this complexity, not only in the number of nodes and structure but also in the increased heterogeneity of protocols and mechanisms[4]. Therefore, integrating heterogeneous IoT entities into different types of CEV applications raises technical challenges regarding design complexity and sustainability issues.

In the actual operation process, due to the lack of a thorough and clear understanding of the complexity of the Cloud-Edge-Vehicle (CEV) architecture, the operation and maintenance are facing tremendous pressure. When optimizing the design of the VECS architecture, it is not easy to control the critical links due to the lack of qualitative and quantitative analysis methodology in terms of system complexity. Therefore, finding an effective method to assess complexity plays an important role in conducting the architecture design. Furthermore, it will provide scientific measures for designers, relieve the pressure of operation and maintenance, and improve the safety control ability of the critical links.

A complex network is characterized by multiple dynamic factors such as changing topology and flows, and precisely correct to assess the complexity of evolving, adaptive and complex CEV architecture[5]. Enlightened by the strengths of complex network theory, we proposed a novel Cloud-Edge-Vehicle architecture for VECS. We correspondingly mapped the multiple layers into cyber-physical networks, employing complex network metrics to empower a holistic complexity assessment in VECS.

The concept of entropy was initially used as a state parameter to describe and judge thermodynamics. Then it was rooted in statistical physics and information theory until it was used to describe the complexity of the state of the matter system[6]. Entropy is varied[7, 8] to be the measurement of uncertainty and information. Complexity varies with changes made at the number of possible states of a system, indicating that entropy can be used to measure project size by using states[9]. Therefore, entropy is an effective quantitative measurement for hierarchy system organization. Models based on entropy can be emulated when measuring structural complexity.

Motivated by the concept of information entropy, we propose a methodology based on *K*-order weight entropy to assess the complexity of the Cloud-Edge-Vehicle paradigm for VECS. We abstracted the elements in a complex system as nodes and the interrelationships between elements as edges, providing a hierarchy description method for studying vehicle-road systems. After that, we used the *K*-order structural entropy to derive the difference in the node's importance. Finally, we calculated system entropy according to CEM-KE. The main contributions of this paper are as follows:

- We proposed a deployment Cloud-Edge-Vehicle (CEV) paradigm for VECS, which can be implemented as a hierarchical structure with three tiers: Vehicle tier, Edge tier, and Cloud tier.
- Based on the complex network theory, the CEV paradigm is mapped into cyber-physical networks. We used the *K*-order structural entropy to identify the diversity and heterogeneity of equipment and interfaces relationship.

978-1-6654-4511-5/21/$31.00 ©2021 IEEE
DOI 10.1109/SmartIoT52359.2021.00054

- To provide design guidance to reduce the structural redundancy in multilayer networks, we proposed CEM-KE to assess the entropy of the CEV framework.

The structure of this paper is as follows. In Section 2, we present the research progress in network complexity. In Section 3, we describe how to build CEM-KE and the steps of complexity measurement in detail. In Section 4, a VECS case was used to calculate its structure complexity for explaining the rationality and practicability of the model. In Section 5, we summarize the main work of this paper.

II. RELATED WORK

A. *Complexity of Network*

The notion of complexity is central in many branches of science. Common understanding tells us what is simple and complex. However, formalizing this elusive notion results in a daunting task [10].

Complexity is highly susceptible to variations in the network dynamics, reflected in its underlying architecture where the topological organization of cohesive subsets into clusters. Local interactions between the nodes clustered into subcomplexes generate the flow of information that characterizes the complexity and dynamics of the whole system[11]. Wan et al. [12] shed light on the IP-spatial, temporal, entropy, and cloud service patterns of IoT devices in edge networks and explore these multidimensional behavioral fingerprints for IoT device classification. Wang et al. [13] proposed a quantitative measurement method for the complexity of supply chain networks, measuring the complexity and evolution of ER random networks, small-world networks, and BA scale-free networks. Zhou et al. [14] proposed a robust analysis framework based on complex network theory to explore the robustness of the power system from a methodological perspective. As the basis of complexity management, complexity analysis is used to measure the system complexity for system solution trade-offs. Hu et al. [15] proposed an MBSE approach to support complex analysis using qualitative and quantitative approaches. Lei et al. [16] developed an improved method to measure the complexity of complex networks effectively. For the improved measure, the topology of network is considered, and the scales of network are considered.

B. *Entropy in Complex Network*

Information entropy metrics have been applied to a wide range of problems that were abstracted as complex networks[17]. A wide range of problems, such as social network analysis[18], communications routing, neural networks[19], identification of key players in transaction networks, the vulnerability of power grid networks[20, 21], and city traffic studies, deals with determining the entropy of relational structures, such as complex networks or graphs.

Based on Shannon's information theory, some recent studies have presented the design entropy concept. Menhorn et al. [22] presented design entropy as a measurement for the complexity of a given circuit by resorting to Shannon's information theory, which is mainly used in the digital circuits field rather than the engineering design field. Wu et al. [9] further defined design entropy as a description of the disorder found in design objects. They proposed a design entropy model, which measures the degree of information chaos in a user interface. Ma jing[23] et al. proposed a complexity measurement model of a mechanical product assembly system based on the entropy of the Internet of Things (configuration entropy and interconnection entropy). Farzad F. et al. [21] aimed to evaluate the effectiveness of using entropic complexity as a feature to enhance situational awareness in dynamical systems. The test system is a small-scale microgrid in which a solid-state transformer (SST) is operating under different dynamical conditions. Cai et al. [24] proposed an evolving caveman network that reveals the differences between structure entropy indices by comparing the sensitivities during the evolutionary network process. Based on the Shannon entropy, Yin et al. [25] developed three heuristic rules to measure the utility of adjacent neighbors to each ego in the networks. Then, the fuzzy systems theory was used to convert the utility of each neighbor into the membership functions. To design a more applicable centrality measure, Xu et al. [26] developed two vital node identification algorithms based on node adjacency information entropy. However, few researchers have measured the complexity under large and volatile sets of heterogeneous and independently behaving information entities. Furthermore, research is lacking on the multi-tier VECS system for designers to identify the key link and reduce the structural redundancy in multilayer networks.

III. METHOD FOR EVALUATING THE COMPLEXITY OF VECS

In this part, we first provide an aerial view of VECS. As shown in Fig. 1, the core architecture of VECS consists of a cloud layer, edge layer and vehicle layer. We assume that each vehicle participating in the coordinated control is equipped with OBUs (On Broad Units) to collect vehicular data and wireless transmission facilities. In other words, the proposed method is based on Vehicle-to-Everything (V2X) network.

A. *Architechture of VECS*

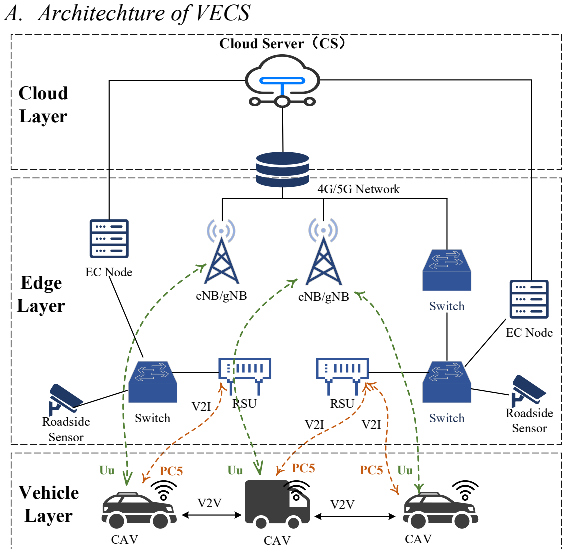


Fig .1 Architechture of VECS

Since the Cloud-Edge-Vehicle (CEV) network links multiple types of devices together to deliver mission-critical industrial services, the complexity assessments for involved devices would be the most fundamental concern. Fig. 1 demonstrates a CEV network for VECS, which can be implemented as a hierarchical structure with three tiers: Vehicle tier, Edge tier, and Cloud tier.

The vehicle tier comprises Connected and Automated Vehicles (CAVs), which are equipped with On-Board Unit (OBU) to communicate with the other varied vehicle and infrastructure. The OBU will send basic vehicle information such as vehicle ID, location, speed, acceleration, fuel consumption, and service request information such as high-definition maps and ramp merging assistance to roadside equipment.

The edge tier consists of Edge Computing nodes (EC nodes), Road-Side Units (RSUs), Road-side Sensors (RSs), switches and eNB/gNB. The primary function of this layer is collecting and processing the information from the vehicle layer. RSU, which is deployed at the end of the road, has a specific communication range in the edge computing layer. The primary function of the RSU is to collect road information, basic vehicle information, service request information and upload the information to the EC nodes. The information transmitted by the RSU in the past needs to be conveyed to the EC node through the 5G base station, such as gNB (5G base station). The EC node includes the transmission link and the edge server, which receives and processes information from RSU.

The cloud tier provides entertainment services such as high-definition map services, music, and high-definition videos in the cloud service layer. Cloud Servers (CSs) have more computing resources and storage resources than edge servers in server hardware. A large amount of global information is stored on the cloud server, such as road information, traffic information, weather information, etc., which can provide high-quality services for vehicles through technologies such as big data processing. It can also calculate traffic flow and determine road congestion based on the vehicle information collected from the edge server.

B. Processing of Information Flow

In the VECS, the basic structure of system management can be divided into the vertical structure and the horizontal structure. Instructions from top to bottom and reports from bottom to top constitute the vertical flow of system information, and each management level divides it in a horizontal direction. The information of the main functional subsystems is connected, which is called the horizontal flow of information, which constitutes a crisscrossed information network.

RSUs collect global basic vehicle road information and service request information and transmit it to the edge cloud server through the 5G base station. The edge cloud server is responsible for storing and updating basic vehicle road information and processing service request information. Also, it decides the request according to the type of service request information, whether the information is processed on the edge server or handed over to the cloud server for processing.

The primary vehicle road information is transmitted to the roadside unit at time intervals. The roadside unit will send the essential information to the edge cloud server through the 5G base station. Then, the data receiving and sending module of the edge cloud server is passed to the message preprocessing module. After that, the processing module delivers this information to the information storage module according to the information identifier. And the information storage module stores this information orderly and deletes the old vehicle information as new basic information enters in the next time interval.

Service request information will only appear when the vehicle initiates a service request. Similarly, the service request information received by a certain RSU will be sent to the edge cloud server through the 5G base station. The data receiving and sending module of the edge cloud server is passed to the message preprocessing module. The message preprocessing module delivers the information to the service module according to the information identifier. The service module will call the corresponding algorithm and the data storage module's data to process the service request and send the decision result to the data receiving and sending module. The data receiving and sending module sends this decision information to the RSU, and the RSU sends this information through the broadcast sending logic to the vehicle.

Information entropy can react to the degree of disorder in the system, and quantitatively analyze and judge the evolution direction of the system. This vehicle-road collaboration-oriented edge system is a typical dissipative system. The dissipative process can be taken as the continuous disintegration of old and new information and the generation of new dissipative systems. This process can be used by the entropy flow in the structural system. And the characteristics of entropy generation.

C. Structure Complexity Measurement Model based on Weighted-Information Entropy

The equipment and interface relationships in the VECS system architecture are all descriptions of the system architecture, reflecting some of the characteristics of the system architecture. However, these two elements cannot be used directly when measuring the structural complexity of the VECS configuration. These two elements must be abstracted to make them meet the requirements of measurement.

Complex network theory abstracts the elements in a complex system as nodes and the interrelationships between elements as edges, providing a straightforward description method for studying complex systems. Therefore, an abstract description of the equipment and the interface relationship between the equipment is required to measure the VECS architecture's structural complexity.

System entropy H_s is a quantitative description of the complex state or chaotic state or degree of order of the system for a generalized system. A system with such characteristics can be described based on the theory of information entropy. The relationship between system elements is random, uncertain, and its manifestation is a disordered, chaotic system. Based on this, system entropy can be extended to the vehicle-road collaboration edge computing system. A description of the evaluation method is given below.

Suppose that total devices in a vehicle-road coordination system are configured under a particular road condition, divided into I types. The configured VCES structure is abstracted into a system node-edge graph G, that is, there are total n nodes in the system node relationship graph, and these nodes can be divided into I types. The set consisting of the i-th type of node in graph G is $Se(E_i)=\{e_{i1},e_{i2},\ldots,e_{ij}\}$, where e_{ij} represents the j-th node in the i-th type of node, $i\in\{1,2,\ldots k,\ldots,I\}$. The entire element set can be express as $S=\{Se(E_1),Se(E_2),\ldots,Se(E_I)\}$. We define $|Se(E_i)|$ as the number of nodes contained in the set $Se(E_i)$, so $j \in [1, |Se(E_i)|], j \in N$.

Referring to Shannon's weight entropy formula, this paper proposed a Complexity Evaluation Method based on Weight Entropy (CEM-WE), which considered the importance of contribution of node and edge. The calculation details in the negative entropy evaluation model are as follows:

$$H_s = -\left(\sum_{i=1}^{I}\left(C_i \times |Se(E_i)| \times p_n(E_i)\log_2 p_n(E_i)\right)\right) + \left(\sum_{i=1}^{I}\left(C_i \times |Se(E_i)| \times p_d(E_i)\log_2 p_d(E_i)\right)\right) \tag{1}$$

$$P_n(E_i) = \frac{|Se(E_i)|}{n} \tag{2}$$

$$P_d(E_i) = \frac{Nd(E_i)}{\sum_i^I Nd(E_i)} \tag{3}$$

$$Nd(E_i) = \frac{\sum_j^{|Se(E_i)|} d(e_{ij})}{|Se(E_i)|} \tag{4}$$

where C_i represents the functional contribution of the i-th type node to the system structure complexity; parameter $p_n(E_i)$ represents the proportion of the i-th type node stones in all equipment (nodes) of the system node relationship; $p_d(E_i)$ represents the weight of the node stone in the system node relationship graph among all interfaces (edges); $Nd(E_i)$ represents the mean value of the number of edges of all the i-th type nodes in graph G; $d(e_{ij})$ represents the number of edges of j-th node in the i-th type.

D. Node Importance based on K-order Structure Entropy

The structural complexity of the VECS can be calculated through the above formula, but the critical node in the architecture that affects the structural complexity cannot be presented. Thus, it is necessary to measure C_i of each device in the edge computing system.

Combining the formula of Shannon entropy, the K-order structure entropy can be defined and figured out to distinguish the differences of the relative importance among nodes[27].

First, we give an unweighted and undirected network graph $G(S,E)$, where the node set is $S = \{Se(E_1), Se(E_2), \ldots, Se(E_I)\}$. For the convenience of calculation, we changed the expression of the set S into $S' = \{e_{11}^1, e_{12}^2, \ldots, e_{ij}^k, \ldots, e_{I|Se(E_I)|}^n\}$, where the elements are arranged in order by k; k represents the k-th element. E is the edge set and suppose L_{kl} as the shortest path length from node e_{ij}^k to e_{mn}^l. To avoid the analysis difference caused by the existence of self-loops in the network, we assume that the node can reach the node itself in 0 steps and defines the number of K-order neighbors of the node as:

$$N_{e_{ij}^k}^K = \sum_{l=1, k\neq l}^{n} I(L_{kl} \le K) + 1 \tag{5}$$

where $I(\cdot)$ is the indicator function, that is, when the $L_{kl} \le K$, $I(\cdot) = 1$, otherwise $I(\cdot) = 0$. From Eq. (5), we can see that for any node, there is $N_{e_{ij}^k}^0 = 1$.

We suppose A is the adjacency matrix of VECS. According to the random matrix theory, the i-th row and j-th column value in matrix A^φ, A to power φ, represents the number of paths connected by φ edges from node v_i to v_j, so $N_{e_{ij}^k}^K$ can also be defined as:

$$N_{e^k}^K = \sum_{l=1, l\neq k}^{n} I\left(\sum_{\varphi=0}^{K} a_{kl}{}^{\varphi} > 0\right) \tag{6}$$

where $a_{kl}{}^{\varphi}$ represents the i-th row and j-th column value in the matrix A^φ. The formula (6) expresses the number of non-zero elements in the i-th row or column vector (the matrix A of the undirected graph is a symmetric matrix, and its polynomial is also symmetric). Therefore, the L_0 norm of the matrix polynomial $A^0 + A^1 + \cdots A^K = \sum_{\varphi=0}^{K} A^\varphi$ is $N_{e^k}^K$, and the Eq.(6) can also be derived as:

$$N_{e^k}^K = \left\| \left(\sum_{\varphi=0}^{K} A^\varphi\right) \cdot e_i \right\|_0 = \left\| \sum_{\varphi=0}^{K} A^\varphi \cdot e_i \right\|_0 \tag{7}$$

where $\|\cdot\|_0$ represents the L_0 norm of the vector; e_i represents an n-dimensional vector with the i-th component being 1 and the remaining components being 0.

The size of the actual network is usually limited. When the K is greater than the graph diameter d of the network, any propagated node is used as the source link to spread the information, and the number of propagated nodes in the network will no longer change. Since the value K is discrete and a non-negative integer, there is $K \in \{0, 1, \ldots, d\}$, where d is named the maximum propagation time, K is also named the propagation time.

To evaluate the importance of nodes, the K-order structure entropy method believes that within a limited propagation time d (note the difference with the propagation time K), the more node in the network caused by a particular node as the source of info propagation, the higher the importance of the node.

Now assuming that the limited propagation time is d, and taking nodes $v_1, v_2, \ldots, v_n$ as the source of propagation, the K-order propagation numbers are respectively $N_{e^1}^K, N_{e^2}^K, \ldots, N_{e^n}^K$, which can represent each node's importance. To evaluate the difference in importance between nodes, that is, the degree of dispersion of $N_{e^1}^K, N_{e^2}^K, \ldots, N_{e^n}^K$, this paper introduced the K-order structural entropy H^K [27] of the network based on Shannon entropy, which can be calculated as:

$$H^K = -\sum_{k=1}^{n} \frac{N_{e_{ij}^k}^K}{\sum_{l=1}^{n} N_{e_{ij}^l}^K} \log_2\left(\frac{N_{e_{ij}^k}^K}{\sum_{l=1}^{n} N_{e_{ij}^l}^K}\right) \tag{8}$$

It can be seen from Eq. (8) that the larger the value of H^K, the smaller the difference between $N_{e^1}^K, N_{e^2}^K, \ldots, N_{e^n}^K$; when $N_{e^1}^K = N_{e^2}^K = \ldots = N_{e^n}^K$, the H^K get the maximum value as log(n). If the importance of nodes is evaluated according to this, there will be no discrimination, and the result is invalid.

Based on focusing on the limited propagation time with large differences in node importance, the weighted summations $N_{e^1}^K, N_{e^2}^K, \ldots, N_{e^n}^K$ are carried out. We defined $Q_{e_{ij}^k}^i$ as the importance of node e_{ij}^k belonged to *i*-th type.

The *K*-order propagation number usually increases with the increase of K. To avoid the large *K*-order propagation number concealing the information with small value, this paper took $N_{e^1}^K, N_{e^2}^K, \ldots, N_{e^n}^K$ mapping to the interval [0,1]. The results are that only the relative order of node importance is examined.

The calculation process is shown as follow:

$$Q_{e_{ij}^k}^i = \sum_{K=0}^{d} c^K \cdot S_{e_{ij}^k}^K \tag{9}$$

$$S_{e_{ij}^k}^K = \frac{N_{e_{ij}^k}^K - \min(N^K)}{\max(N^K) - \min(N^K)} \tag{10}$$

$$c^K = 1 - \frac{H^K - \min(H)}{\max(H) - \min(H)} \tag{11}$$

$$C_i = \frac{\sum_{j=1}^{|Se(E_i)|} Q_{e_{ij}^k}^i}{\sum_{k=1}^{n} Q_{e_{ij}^k}^i} \tag{12}$$

where $S_{e_{ij}^k}^K$ is the result of normalization from $N_{v_i}^K$; c^K is weight coefficient.

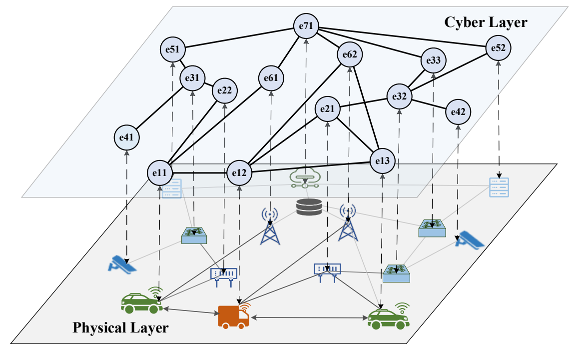
IV. Example Calculation and Result Analysis of the Vehicle-Road Coordination System

To verify the rationality and practicability of the CEM-WE, we take the architecture design from Fig. 1 as a calculation example. We have attempted to sketch the framework of mapping the VECS architecture to a multilayer complex network by providing a Cloud-Edge-Vehicle computing paradigm. The proposed framework demonstrated in Fig. 1 could be divided adequately into cyber and physical network layers. In Fig. 2, the physical layer of VECS has been abstracted into a node-edge cyber topology, where the devices are mapping to nodes, and the communication interfaces are mapping to edges. The cyber layer illustrated the node-edge topological graph of devices and interfaces.

In Fig.2, the deep integration of the internet of the vehicle and the information network has formed a vehicle-road information physical system. The solid black lines in the figure represent the internal connection edges of the network, including the transmission lines on the internet of the vehicle and the communication lines in the information network. The connecting edges between the networks are shown as the black dashed line. The two networks interact with each other through information transmission or energy exchange.

Inspired by the disease infection model[28], this analysis will combine the complex network to abstract the most straightforward information transmission process. The propagated node cannot receive information from the previous node.

When measuring the importance of nodes, a more commonly used method is to set each node as the source of information for propagation and use the total time taken for all nodes in the network to be transformed into propagated nodes as the evaluation index of node importance. The less time it takes, the more important the node is. According to Eq. (7), we first established the adjacent matrix A of Fig. 2 and obtained the diameter d is 6. Then we could get the K-order propagation number matrix of the network, as shown in Fig. 3. According to Eq. (12), we calculated the functional contribution of each node in the system.



(1)CAVs: e11 e12 e13 (2)RSUs: e21 e22 (3)Switches: e31 e32 e33
(4)Roadside Sensors: e41 e42 (5)EC Nodes: e51 e52 (6)eNB/gNBs: e61 e62
(7)Cloud Server: e71

Fig. 2. The Cyber-physical multilayer network of VECS

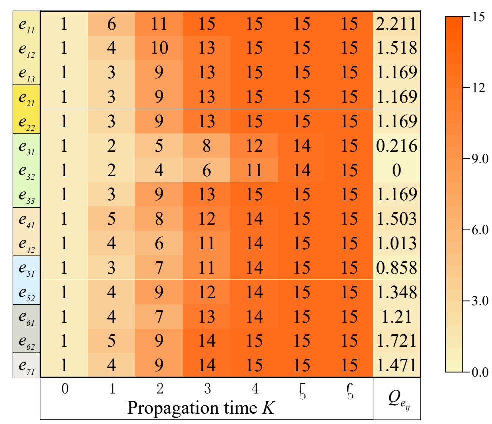


Fig. 3. *K*-order propagation number matrix: K-order propagation number obtained with different nodes as the source of information.

In Fig.2, the elements of VECS are divided into seven types. Then, we calculated the structural complexity parameters of 7 types. The results are shown in Table I.

TABLE I. STRUCTURAL COMPLEXITY PARAMETERS OF VECS

E_i	*Devices*	$\lvert Se(E_i)\rvert$	$Nd(E_i)$	$P_n(E_i)$	$P_d(E_i)$	C_i
E_1	CAV	3	3.333	0.200	0.172	0.248
E_2	RSU	2	2.500	0.133	0.129	0.124
E_3	Switch	3	3.000	0.200	0.155	0.208
E_4	RS	2	1.000	0.133	0.052	0.012
E_5	EC Node	2	2.000	0.133	0.103	0.132
E_6	eNB/gNB	2	2.500	0.133	0.129	0.151
E_7	CS	1	5.000	0.066	0.259	0.125

According to the structural complexity formula Eq. (1), we figure out the system entropy of VECS:

$$H_s = -\left(\sum_{i=1}^{I}\left(C_i \times |Se(E_i)| \times p_n(E_i)\log_2 p_n(E_i)\right)\right) - \left(\sum_{i=1}^{I}\left(C_i \times |Se(E_i)| \times p_d(E_i)\log_2 p_d(E_i)\right)\right) = 1.946$$

To provide design guidance to reduce the structural redundancy in multilayer networks, we analyzed the complexity of various topologies and calculated their system entropies respectively in Table II. Based on the architecture design principle in VECS, each vehicle is connected to at least one RSU and one gNB. Therefore, we expanded the original topology Fig. 4(a) with edge pairs: (e_{12}, e_{22}), (e_{11}, e_{21}) and (e_{13}, e_{22}) into a new topology Fig. 4(b). To remove the complexity of ad-hoc vehicle networks, the topology in Fig. 4(c) removed the vehicle-to-vehicle connections, which are the edge pairs (e_{11}, e_{11}) and (e_{12}, e_{13}). Finally, we considered a complicated scenario shown in Fig. 4(d), where the vehicles connect all the edge devices and other vehicles.

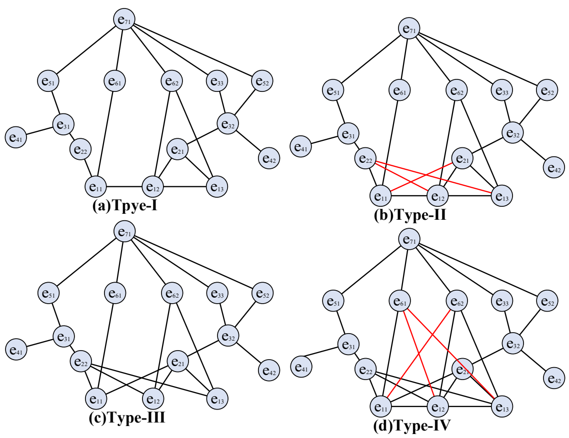


Fig. 4. Four various topologies of VECS

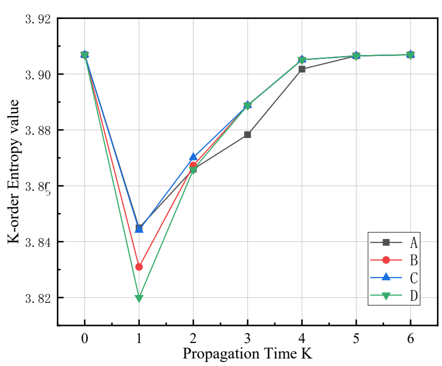


Fig. 5. The K-order entropy value of four types

According to Table II, the proposed CEM-WE could distinguish the complexity of different topological configurations. We found Type-III topology had the minimum system entropy value of 1.929 among the four types. Therefore, from the perspective of the complexity of the Cloud-Edge-Vehicle system architecture, it is recommended to adopt Type-III topology when operating and maintaining or optimizing the system architecture in the future.

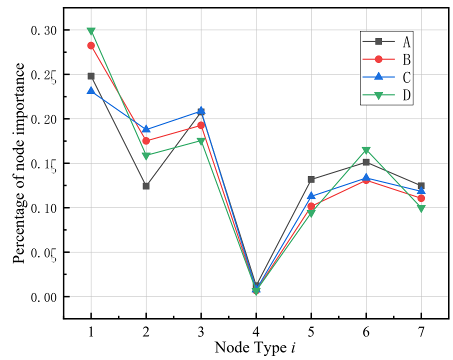


Fig. 6. The percentage of importance coefficients

TABLE II. SYSTEM ENTROPY OF FOUR TYPES OF VECS

Topology	Type-I	Type-II	Type-III	Type-IV
H_s	1.946	2.003	1.929	2.028

V. CONCLUSION

This paper proposes a complexity evaluation method of the vehicle-road collaborative edge computing system based on weighted structural entropy. We exploit the *K*-order structural entropy to identify the heterogeneity of equipment and the difference between interface importance. The weight coefficient is divided into equipment type weight and node importance weight.

In the practical application, according to the number of connected vehicles and RSU range of applications, CEM-KE could build complex network models with different topological characteristics in the vehicle-road edge computing system. The structural entropy-based evaluation method was used to analyze the structure of VECS, which could quantitatively express the order degree of VECS system structure and provide the theoretical basis for the structural optimization of edge computing architecture. The future work can be extended to map the more complex network topology in the real world to the corresponding Cloud-Edge-Vehicle paradigm.

ACKNOWLEDGMENT

This work was supported by China National Key Research and Development Program(NO.2018YFE0197700).

REFERENCES

[1] M. Z. A. Bhuiyan, S.-Y. Kuo, J. Cao, and G. Wang, "Guest Editorial: Trustworthiness in Industrial Internet of Things Systems and Applications," *IEEE Transactions on Industrial Informatics,* vol. 16, pp. 6079-6082, 2020.

[2] B. Vogel-Heuser, and D. Hess, "Guest editorial Industry 4.0–prerequisites and visions," *IEEE Transactions on Automation Science and Engineering,* vol. 13, no. 2, pp. 411-413, 2016.

[3] W. Yu, F. Liang, X. He, W. G. Hatcher, C. Lu, J. Lin, and X. Yang, "A survey on the edge computing for the Internet of Things," *IEEE access,* vol. 6, pp. 6900-6919, 2017.

[4] J. P. Sterbenz, "Smart city and IoT resilience, survivability, and disruption tolerance: Challenges, modelling, and a survey of research opportunities," in 2017 9th International Workshop on Resilient Networks Design and Modeling (RNDM), Alghero, Sardinia, IT, 2017, pp. 1-6.

[5] G. Peng, H. Wang, H. Zhang, and K. Huang, "A hypernetwork-based approach to collaborative retrieval and reasoning of engineering design knowledge," *Advanced Engineering Informatics,* vol. 42, pp. 100956, 2019.

[6] F. X. Costa, and P. Pessoa, "Entropic dynamics of networks," *arXiv preprint arXiv:2102.02355*, 2021.

[7] E. Aghamohammadzadeh, M. Malek, and O. F. Valilai, "A novel model for optimisation of logistics and manufacturing operation service composition in Cloud manufacturing system focusing on cloud-entropy," *International Journal of Production Research,* vol. 58, no. 7, pp. 1987-2015, 2020.

[8] D. Mateos, R. G. Erra, R. Wennberg, and J. P. Velazquez, "Measures of entropy and complexity in altered states of consciousness," *Cognitive neurodynamics,* vol. 12, no. 1, pp. 73-84, 2018.

[9] L. Wu, J. Li, and T. Lei, "Design entropy: a new approach for evaluating user experience in user interface design," *Advances in Ergonomics in Design*, pp. 583-593: Springer, 2016.

[10] D. Felice, S. Mancini, and M. Pettini, "Quantifying networks complexity from information geometry viewpoint," *Journal of Mathematical Physics,* vol. 55, no. 4, pp. 043505, 2014.

[11] V. Berec, "Complexity and dynamics of topological and community structure in complex networks," *The European Physical Journal Special Topics,* vol. 226, no. 10, pp. 2205-2218, 2017.

[12] Y. Wan, K. Xu, F. Wang, and G. Xue, "Characterizing and mining traffic patterns of IoT devices in edge networks," *IEEE Transactions on Network Science and Engineering,* vol. 8, no. 1, pp. 89 - 101, 2020.

[13] H. Wang, T. Gu, M. Jin, R. Zhao, and G. Wang, "The complexity measurement and evolution analysis of supply chain network under disruption risks," *Chaos, Solitons & Fractals,* vol. 116, pp. 72-78, 2018.

[14] D. Zhou, F. Hu, S. Wang, and J. Chen, "Power network robustness analysis based on electrical engineering and complex network theory," *Physica A: Statistical Mechanics and its Applications,* vol. 564, pp. 125540, 2021.

[15] Z. Hu, J. Lu, J. Chen, X. Zheng, D. Kyritsis, and H. Zhang, "A complexity analysis approach for model-based system engineering," in 2020 IEEE 15th International Conference of System of Systems Engineering (SoSE), 2020, pp. 000501-000506.

[16] M. Lei, L. Liu, and D. Wei, "An Improved method for measuring the complexity in complex networks based on structure Entropy," *IEEE Access,* vol. 7, pp. 159190-159198, 2019.

[17] Y. M. Omar, and P. Plapper, "A survey of information entropy metrics for complex Networks," *Entropy,* vol. 22, no. 12, pp. 1417, 2020.

[18] T. Wen, and Y. Deng, "The vulnerability of communities in complex networks: An entropy approach," *Reliability Engineering & System Safety,* vol. 196, pp. 106782, 2020.

[19] N. Caticha, "Entropic dynamics in neural networks, the renormalization group and the hamilton-jacobi-bellman equation," *Entropy,* vol. 22, no. 5, pp. 587, 2020.

[20] L. Li, Z. Li, Y. Liu, Z. Xiao, Y. Cai, and F. Liu, "Vulnerability analysis of cyber-physical system based on improved structural entropy," in 2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2), Wu Han, China, pp. 761-765.

[21] F. Ferdowsi, M. Hosseini, and M. Hosseini, "Classification of emergent dynamics in microgrids utilizing an entropic complexity-based feature extractor," *Data-Enabled Discovery and Applications,* vol. 4, no. 1, pp. 1-10, 2020.

[22] B. Menhorn, and F. Slomka, "Design entropy concept: a measurement for complexity," in 2011 Proceedings of the seventh IEEE/ACM/IFIP international conference on Hardware/software codesign and system synthesis(CODES+ ISSS), Taipei Taiwan, 2011, pp. 285-294.

[23] J. Ma, M. Liu, Q. Wang, L. Ling, and M. Zhang, "Complexity metrics for assembly system of mechanical products based on IOT-entropy," *Computer Integrated Manufacturing Systems*, pp. 01, 2016.

[24] M. Cai, Y. Cui, and H. E. Stanley, "Analysis and evaluation of the entropy indices of a static network structure," *Sci Rep,* vol. 7, no. 1, pp. 9340, Aug 24, 2017.

[25] L. Yin, and Y. Deng, "Toward uncertainty of weighted networks: An entropy-based model," *Physica A: Statistical Mechanics and its Applications,* vol. 508, pp. 176-186, 2018.

[26] X. Xu, C. Zhu, Q. Wang, X. Zhu, and Y. Zhou, "Identifying vital nodes in complex networks by adjacency information entropy," *Scientific reports,* vol. 10, no. 1, pp. 1-12, 2020.

[27] L. Huang, Y. Huo, Q. Wang, and X.-F. Cheng, "Network heterogeneity based on K-order structureentropy," *Acta Physica Sinica,* vol. 68, no. 01, pp. 325-336, Dec. 2019, 2019.

[28] L. Zhu, G. Guan, and Y. Li, "Nonlinear dynamical analysis and control strategies of a network-based SIS epidemic model with time delay," *Applied Mathematical Modelling,* vol. 70, pp. 512-531, 2019.