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EDITORIAL

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Edge intelligence-enabled cyber-physical systems

1 | INTRODUCTION

With the advent of the Internet of everything era, people's demand for intelligent Internet of Things (IoT) devices is steadily increasing. A more intelligent cyber-physical system (CPS) is needed to meet the diverse business requirements of users, such as ultra-reliable low-latency communication, high quality of services (QoS), and quality of experience (QoE).[1] Edge intelligence (EI) is recognized by academia and industry as one of the key emerging technologies for the CPS, which provides the ability to analyze data at the edge rather than sending it to the cloud for analysis, and will be a key enabler to realize a world of a trillion hyperconnected smart sensing devices.[2]

As a distributed intelligent computing paradigm in which computation is largely or completely performed at distributed nodes, EI provides for the rapid development of artificial intelligence (AI) and edge computing resources to support real-time insight and analysis for applications in CPS, which brings memory, computing power and processing ability closer to the location where it is needed, reduces the volumes of data that must be moved, the consequent traffic, and the distance the data must travel.[3] As an emerging intelligent computing paradigm, EI can accelerate content delivery and improve the QoS of applications, which is attracting more and more research attentions from academia and industry because of its advantages in throughput, delay, network scalability and intelligence in CPS.[4]

EI-enabled CPS integrates and merges multiple disciplines. EI-enabled CPS embodies distributed cooperation and learning intelligence, and provides fast intelligent autonomous response at the edge. Thus, it is an example of the emerging paradigm of distributed intelligent systems and has become one of the most popular trends in smart industry, agriculture, healthcare, home, transportation and so forth.[5] Since EI-enabled CPS provides novel distributed computing and processing ability and enables rapid machine-to-machine communication and machine-to-human interaction, EI assisted IoT takes localized processing farther away from the network right down to the sensor by pushing the computing processes even closer to the data sources, which also provides multidisciplinary novel solutions and interactions to improve QoS and QoE.[6]

It is clear that EI-enabled CPS promotes a large class of applications and has emerged with a great potential to change our lives and improve user's QoE. However, EI also brings us new challenges, such as costs, communications, data moving and management, security and privacy issues.

The objective of this special issue is to present a collection of high-quality research papers that report the latest research advances addressing the related challenges and perspectives in the area of EI-enabled CPS. Our goal is to shed light on the multifaceted aspects of this emerging system, including system model and architecture, hardware accelerators, network virtualization, computation offloading and mobility management, intelligent learning techniques, data sensing, fusion, moving and management, multimedia analytics and processing, low-cost communication, QoS and QoE improvements, security and privacy, as well as novel applications, case studies and test beds. After a rigorous and careful review process performed by reviewers and the Guest Editors, 8 papers, from an open call and the 13th IEEE/ACM International Conference on Utility and Cloud Computing (UCC2020), have been accepted addressing the subjects classified in the following categories: (i) data sensing, management and resource allocation; (ii) privacy and security; and (iii) novel applications.

2 | CONTENT

2.1 | Data sensing, management and resource allocation

As a multi-dimensional complex system, the EI-enabled CPS integrates computing, network and physical environments and provides the ability to analyze data at the edge rather than sending it to the cloud. Therefore, how to effectively sense and manage data is crucial to improve the performance of CPS.

Cognitive radio (CR) can effectively solve the problem of spectrum scarcity through dynamic spectrum allocation. However, shadowing effects and multipath fading severely affect the sensing performance of users in the CPS. To improve the sensing performance of the CPS, Zhang et al.[7] proposed a soft fusion-based cooperative spectrum sensing algorithm, which adopts improved particle swarm optimization (IPSO) to find the optimal weighting coefficients for soft fusion. IPSO maintains the diversity of particles by introducing an immune algorithm and chaotic sequence mechanisms to speed up the convergence of the algorithm. In addition, to maintain the balance between the search ability and convergence of the IPSO, the IPSO adaptively adjusts the inertia weight according to the convergence of particles.

The emergence of EI enables edge devices to be applied in various fields to provide fast response services for latency-sensitive users. At the same time, EI also generates a huge amount of data. How to effectively manage services and improve service search efficiency is a major challenge. The multilevel index model (MIM) can efficiently discover services while managing large amounts of data. However, it is a new challenge to efficiently update the MIM by adding new services in a timely and accurate manner in the EI-enabled CPS environment. To solve the above problems, Gu et al.[8] proposed an optimized multilevel index model. This model employs a designated key selection method that reduces service addition time without affecting service retrieval performance.

Cloud computing has become an indispensable auxiliary technology for EI-enabled CPS due to its powerful computing ability and high concurrency. However, the resource and task scheduling issues of cloud computing limit the utilization and load balancing performance of CPS. How to coordinate the task and resource allocation of cloud computing in CPS is a challenge that needs to be solved urgently. To fully search the solution space and generate optimal task assignments, Chen et al.[9] presented a linear programming-based resources and tasks model. Then, a population-based approach, which was inspired by the differential evolution method, has been proposed to assign appropriate resources to tasks and minimize the total time cost.

2.2 | Privacy and security

EI-enabled CPS revolutionizes the development of new computing paradigms to facilitate the flow of data and the delivery of content. However, due to the lack of effective security mechanisms and untrusted wireless transmission, large-scale data transmission in CPS faces great security threats and privacy disclosure. Therefore, how to protect the private data in EI-enabled CPS is the key problem that restricts its development.

EI-enabled CPS collects physiological data from patients through technologies such as wireless sensor networks, radio frequency identification and wearable devices. Then, the system analyzes the collected data for early diagnosis and treatment. Doctors can also perform remote monitoring or remote surgery through the system. However, the patient's body data is often highly confidential, which poses significant challenges to the privacy protection of medical data. In Reference 10, Deebak et al. proposed a lightweight privacy-aware secure authentication (LPASA) scheme to address security breaches in medical data. LPASA utilizes lightweight cryptographic operations such as a one-way hashing function and bitwise exclusive-OR to improve security efficiency. In addition, they presented formal and informal security analyses to verify the security efficiency of LPASA.

EI-enabled CPS is able to process data at the edge, providing fast response capabilities and high concurrency. However, the implementation weakness of EI devices also opens a new avenue of security threats. Attackers can exploit security vulnerability from side channels with the development of machine learning technology. This vulnerability will become more and more serious. Mukhtar et al.[11] proposed a deep learning-based evaluation system integrated at the edge device to detect side channel leaks when edge devices deploy new security algorithms for updating. The model is trained in the cloud and deployed at the edge after the training is completed. It can be part of the edge device, or an independent module for edge analysis.

2.3 | Novel applications

With the advances of EI, EI-enabled CPS allows operators to flexibly and rapidly deploy innovative applications and various intelligent services, especially with the latest innovation in social networks, deep learning and big data techniques, which will further support future vision of the CPS to create inherent intelligence. Therefore, EI-enabled CPS also plays a significant role in various fields.

The online social networks consisting of extensive network nodes and the links between them are an essential part of future CPS. However, the existing community discovery algorithms cannot effectively find overlapping communities in social networks, resulting in poor network construction performance. To improve the efficiency of overlapping community discovery, Ge et al.[12] proposed an edge intelligence-enabled dynamic overlapping community discovery and evolution prediction model (EIDEP). EIDEP employs a label propagation algorithm based on extension (LP AE) algorithms to discover user community structures in online social networks. Moreover, to quickly and accurately realize the community evolution of online social networks, EIDEP incorporates a user interest behavior-based evolution prediction (UIBEP) algorithm based on the LPAE algorithm.

EI-enabled CPS integrates sensing, computing and storage, equipping IoT devices the ability to analyze at the edge and accelerate content processing, which is the key driving force to achieve an interconnected world of a trillion smart devices in the future. In image style transfer tasks, the stacking of neural networks often has redundancy, resulting in slow computation and high memory usage. To address the above problems, Liu et al.[13] proposed an improved convolutional neural networks (CNN)-based resolution enhancement scheme in the CPS, which includes a style transfer network (RESTN) model and a two-stage neural network training method. In the first stage of training, low-resolution and high-resolution images are utilized to improve the resolution enhancement ability of RESTN. In the second stage of training, the scheme shares the parameters of feature extraction to learn different styles and adopts the octave convolution operation to reduce model redundancy.

Supply chains bring new forms of cooperation between enterprises and users, which become the core part of enterprises in market competition. Compared with the traditional supply chain financial model, EI-enabled CPS brings changes to the supply chain in four aspects: credit evaluation, risk protection, credit cycle and punishment mechanisms. In Reference 14, Yin et al. analyzed in detail the operation mechanism of combining edge intelligence and traditional supply chain financing, and proposed an EI-enabled supply chain financial model based on Business-to-Business (B2B) platforms, which builds a cost–benefit model for different users from a financial perspective. Moreover, other key parts of the B2B platform also are explored, including the selection of financing objects, strategy formulation, optimization decision-making, and incentive mechanism. This model provides a solution for the combination of EI-enabled CPS and supply chain finance models.

3 | CONCLUSIONS

In conclusion, the papers included in this special issue show the diversity of research being conducted in the field of EI-enabled CPS and novel applications. While this issue offers limited contributions to this field, we strongly believe that it has opened the door for more involved research in this important area of research.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest regarding the publication of this article.

DATA AVAILABILITY STATEMENT

No data are available.

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REFERENCES

1. Zhou Y, Yu FR, Chen J, Kuo Y. Cyber-physical-social systems: a state-of-the-art survey, challenges and opportunities. *IEEE Commun Surveys Tutorials*. 2020;22(1):389-425.
2. Letaief KB, Shi Y, Lu J, Lu J. Edge artificial intelligence for 6G: vision, enabling technologies, and applications. *IEEE J Selected Areas Commun*. 2022;40(1):5-36.
3. Deng S, Zhao H, Fang W, Yin J, Dustdar S, Zomaya AY. Edge intelligence: the confluence of edge computing and artificial intelligence. *IEEE Internet Things J*. 2020;7(8):7457-7469.
4. Liu Y, Peng M, Shou G, Chen Y, Chen S. Toward edge intelligence: multiaccess edge computing for 5G and internet of things. *IEEE Internet Things J*. 2020;7(8):6722-6747.
5. Ghosh AM, Grolinger K. Edge-cloud computing for internet of things data analytics: embedding intelligence in the edge with deep learning. *IEEE Trans Ind Informat*. 2021;17(3):2191-2200.

6. Gómez-Carmona O, Casado-Mansilla D, López-de-Ipiña D, García-Zubia J. Optimizing computational resources for edge intelligence through model Cascade strategies. *IEEE Internet Things J*. 2022;9(10):7404-7417.
7. Zhang J, Xiao X. Soft fusion-based cooperative spectrum sensing using particle swarm optimization for cognitive radio networks in cyber-physical systems. *Concurrency Computat Pract Exper*. 2023;35(13):e6295.
8. Jiayan G, Yan W, Anjum A, Panneerselvam J, Yao L, Yuan B. Optimization of service addition in multilevel index model for edge computing. *Concurrency Computat Pract Exper*. 2023;35(13):e6626.
9. Chen J, Han P, Liu Y, Xiaoyan D. Scheduling independent tasks in cloud environment based on modified differential evolution. *Concurrency Computat Pract Exper*. 2023;35(13):e6256.
10. Deebak DB, AL-Turjman F. Lightweight privacy-aware secure authentication scheme for cyber-physical systems in the edge intelligence era. *Concurrency Computat Pract Exper*. 2023;35(13):e6510.
11. Mukhtar N, Mehrabi A, Kong Y, Anjum A. Edge enhanced deep learning system for IoT edge device security analytics. *Concurrency Computat Prsact Exper*. 2023;35(13):e6764.
12. Ge J, Lei-lei Shi L, Liu HS, Panneerselvam J. Edge intelligence-enabled dynamic overlapping community discovery and evolution prediction in social media data streams. *Concurrency Computat Pract Exper*. 2023;35(13):e6786.
13. Liu X, Li B. Stylized image resolution enhancement scheme based on an improved convolutional neural network in cyber-physical systems. *Concurrency Computat Pract Exper*. 2023;35(13):e6615.
14. Yin F, Yang R, Hongxin Y, Zhou W, Zhao Y, Zhang S. Edge intelligence-enabled supply chain financial model based on business-to-business e-business platforms. *Concurrency Computat Pract Exper*. 2023;35(13):e6353.