Guest Editorial
Special Section on Tiny Machine Learning in Internet of Unmanned Aerial Vehicles

WITH the rapid development of ubiquitous networks and smart devices, artificial intelligence-based unmanned aerial vehicles (UAVs) are drawing more and more attention. The rise in popularity of deep neural networks (DNNs) has spawned a research effort to deploy various kinds of DNN models on vehicles. They have been used to accomplish complicated vehicular tasks and enable the construction of intelligent vehicular networks. Despite the promising prospects, how to train and run them on resource-limited and hardware-constrained UAVs faces huge challenges. Furthermore, the tradeoff between accuracy and latency needs to be considered while reducing the computational cost of DNN training.

In light of these potentials, this special issue invited original and breakthrough research, which advanced the field of tiny machine learning (ML) for Internet of UAVs. After a rigorous peer review done by at least three- and one-round revision (many papers with two-round or three-round revision), only 43 among 114 submissions were accepted. They can be categorized by research focus into three categories: 1) security and privacy; 2) system robustness; and 3) environmental adaptability.

A number of studies have focused on the security and privacy issues in the Internet of UAVs. Wu et al. [A1] proposed a fast location-aware repair strategy for grouped UAV clusters. It is a dynamic repair method aiming at minimizing repair time and cross-group repair traffic. The primary focus is on finding the optimal middle partial decoding nodes to help groups based on the node location, thus minimizing the repair time of each strip. Simulations and local static cluster experimental results have verified its feasibility and effectiveness. Qureshi et al. [A2] considered an asynchronous federated framework for UAV networks by local model training and parameter transmission to a mobile-edge computing (MEC) server, enhancing learning efficiency and addressing data privacy concerns. They present a device selection strategy and a multiagent asynchronous advantage actor–critic-based joint resource allocation algorithm to optimize latency and energy utilization in the Internet of UAVs. Zhang et al. [A3] introduced a novel tiny ML-based noise-tolerant radio frequency fingerprinting system that integrates contrastive learning and data augmentation techniques. The primary objective is to enhance the identification of unauthorized UAVs by improving generalization ability. The augmentation technique is employed to enhance legitimate training data sets, particularly under varying signal-to-noise ratios. Furthermore, they introduced a novel contrastive loss criterion designed to capture relevant information from the collected samples.

Pauu et al. [A4] introduced a decentralized graph federated learning (FL) method to process distributed learning for a huge number of interconnected nodes in a graph network. It comprises three main phases: 1) utilizing stochastic gradient descent with differential privacy for local model training on UAVs to safeguard sensitive information; 2) leveraging blockchain for secure and efficient model weight sharing; and 3) implementing a dedicated proof-of-stake consensus mechanism for validator selection and model weight aggregation. Their method aims to balance privacy protection and model accuracy while ensuring low latency, communication, and computational efficiency. To address the privacy and security issues caused by environmental dynamics, Wang et al. [A5] proposed a joint FL computing offloading technique based on edge intelligence. A multilayer perceptron is employed to learn the characteristics of computational tasks and transfer different tasks to different smart devices. Considering that task publishers in existing FL incentive methods are boundedly rational under risky conditions, Fu et al. [A6] proposed a prospect theory-based incentive mechanism for UAV networks. They used prospect theory to model the risk-aware behavior of task publishers and construct a subjective utility model. Then, they utilized the framing effect of the prospect theory to design the optimal contract to maximize subjective utility.

Wu et al. [A7] focused on the network security issues of UAVs and established a targeted intrusion detection system. They developed an improved fuzzy rough set model based on adaptive neighborhoods. They employed a feature selection method to select optimal features and reduce the overall computational cost of the intrusion detection system. Furthermore, they proposed a tiny intrusion detection model that achieves high-precision detection via shallow deep learning (DL). Liu et al. [A8] combined local search and iterative optimization to jointly optimize data collection locations and visitation sequences for the Internet of UAVs. Virtual nodes are introduced, enabling the Internet of UAVs to dynamically avoid high-risk areas. An online virtual node selection algorithm leveraging tiny ML models supports real-time trajectory re-evaluation and adjustment to improve flight safety. Considering the high heterogeneity and limited resources in

Digital Object Identifier 10.1109/JIOT.2024.3396928

UAV networks, Zhou et al. [A9] proposed a community-based hierarchical framework for privacy preservation and poisoning elimination of fairness-aware FL in heterogeneous UAV networks. First, they divided UAV nodes based on cross-participant similarity and task-oriented fitness to obtain peer communities and coworker ones. Then, they integrated community-specific differential privacy into the mutually reliable fairness-aware FL process to achieve both privacy amplification and efficient individual collaborative training.

Zhu et al. [A10] proposed a secure message transmission scheme and location obfuscation to address security and privacy threats in large-scale UAV communications. Their scheme utilizes reinforcement learning (RL) to generate stable propagation paths and employs position obfuscation techniques to conceal the relative positions of UAVs. To mitigate access issues posed by malicious nodes, a message authentication-based encryption technique is employed to encrypt transmitted data and prevent forgery. Kang et al. [A11] formulated a game model to capture the interaction between roadside units and UAVs by incorporating the immersion metric into the utilities of UAVs for the detailed understanding of user experiences. Additionally, they proposed a tiny multiagent deep RL (DRL) algorithm by leveraging pruning techniques to efficiently approximate Stackelberg equilibrium. By combining DRL with pruning, their algorithm can effectively handle complex environments, thus improving overall performance in resolving Stackelberg games for UAV twin migration. Zhou et al. [A12] investigated the transferability of adversarial attacks in the context of scaling tiny ML to reduce security risks in the Internet of UAVs. They measured the transferability of adversarial attacks and explored the methods to enhance their transferability and effectiveness. The methodology provides visualizations that vividly illustrate the impact of adversarial instances, facilitating an intuitive exploration and analysis of results. Zheng et al. [A13] introduced a trustworthy, low-latency, energy-efficient tiny wireless FL framework with blockchain for the Internet of UAVs. They presented a model to quantify the trustworthiness of devices, incorporating communication, computation, and block production time with a decay function per FL round at UAVs. The proposed model aggregates trust information from various UAVs based on their trust recommendation credibility, which is further formulated as an optimization problem to balance trustworthiness, learning speed, and energy consumption across tiny IoT devices with varying capabilities.

The second category of papers focuses on enhancing the system robustness of the Internet of UAVs. To address the challenges posed by complex urban environments and hardware limitations of UAVs, Xi et al. [A14] proposed a lightweight soft actor–critic algorithm to optimize the model training process, network architecture, and algorithmic model. To enhance feature loss and learning efficiency, they introduced a cross-layer connection method. They adopted adaptive temperature coefficients to realize dynamic UAV exploration probabilities. Wu et al. [A15] proposed a cross-platform adaptive weight compression approach for DNN models to accommodate different smart devices and enhance the reliability of intermediate model weight transmission. They encapsulated binary weights into self-contained dynamic batch-like transactions to decrease encoding and decoding overhead. Finally, they gave a quantile-based histogram sketch to compress the intermediate model by using constrained space. Li et al. [A16] focused on topology control in UAV swarm ad-hoc networks. They designed a centroid-guided target-driven method to transform arbitrary graphs into 2-connected graphs. Furthermore, they proposed a topology control method based on this approach to generate 2-connected network topologies suitable for topology construction and adjustment.

Hu et al. [A17] designed a lightweight multitype data blockchain architecture to cater to the specific requirements of low-latency query services and cost-effective resource utilization in massive Internet of UAV systems. They incorporated innovative cross-layer lightweight multitype blocks in their architecture. Resource-constrained UAVs maintain lightweight block headers, fog nodes store block bodies with high query probability, and less frequently accessed data is offloaded to cloud storage. A cost-effective block scheduling scheme is proposed to optimize the storage and querying costs. This scheme adopts a cooperative DRL algorithm to effectively schedule lightweight multitype blocks between the fog and cloud layers. To enhance UAV coverage and reduce energy consumption, Jia et al. [A18] proposed a path-planning method with bidirectional forwarding path coverage for optimizing UAV flight trajectories. They merged the subconvex region and weighted traversal of the graph to decrease the computational cost of obtaining complete paths. Zhang et al. [A19] investigated the optimization of brain–computer interfaces in UAV-assisted IoT. To improve the lightness and accuracy of the model on intelligent vehicles, they proposed a lightweight self-attentive augmentation model to decode universal brain control intentions between UAVs and intelligent vehicles and construct a data set of vehicular brain-controlled intentions. Liu et al. [A20] constructed a system where UAV serves as a mobile charger for replenishing sensor energy and the mobile utility vehicle acts as a mobile base station for replacing the UAV's battery. The primary objectives are to minimize sensor downtime and optimize UAV energy consumption. To address this problem, they adopted a multiobjective deep Q-network (DQN) algorithm.

Kong et al. [A21] transformed the path planning of UAVs into an optimization problem and proposed a multiagent deep deterministic policy gradient-based algorithm for UAV trajectory planning. To further reduce the overall energy usage, they introduced the "tiny one," an enhanced variant achieved through pruning and reducing hidden layer nodes. This approach can reduce UAV energy consumption by reducing computational cost, thereby improving UAV flight time and data collection duration. To achieve energy-efficient split inference in UAVs with multiple tasks, Zhao et al. [A22] proposed a two-timescale approach. Specifically, the discrete and continuous variables are divided into two timescales to reduce the size of the action space and computational complexity, allowing for the utilization of tiny RL in selecting discrete transmission modes for sequential tasks. An optimization technique is incorporated between the output and a reward function to optimize continuous transmission power. To further reduce computational complexity, an algorithm is proposed to minimize transmission power in each time slot.

By minimizing the transmission time of each task, which results in a monotonic decrease in energy consumption, the minimal transmission power can be achieved. To address model aging, Zheng et al. [A23] presented an enhanced scheme for detecting TinyML-based container escapes based on semantic associations of syscalls. First, they efficiently gathered multidimensional syscall data from UAV networks by using the designed eBPF-based data collection framework. After that, the time window sliding algorithm is employed to identify the most relevant multidimensional data related to escape behaviors. Finally, the performance of existing detectors is improved through feature encoding and clustering techniques.

Chen et al. [A24] proposed an expert hybrid model architecture to optimize system utility to address the issue of giant models unable to meet computational and memory requirements on UAVs. They decoupled the giant model into multiple micro-experts and enabled UAVs to dynamically select the best matched expert. In the scenario of multiple edge servers with multiple UAVs, the selection of experts and the association of UAVs are two central issues. The authors propose a graph learning-based solution to address them by learning the complex interactions among edge servers, UAVs, and their required experts, thereby maximizing system utility. Zhong et al. [A25] proposed a novel lightweight federated graph learning (FGL) framework to accelerate the inference speed of classification models in UAV-assisted MEC systems with limited computing and storage resources. They designed an adaptive subgraph generator to obtain well-compressed subgraphs. To alleviate the pressure of resource-constrained UAV-assisted MEC systems, they introduced a lightweight graph convolutional model as the local node classifier in FGL, simplifying the feature propagation of graph neural networks into a multiclass logistic regression, thereby accelerating local training and inference.

Liu et al. [A26] proposed a mobility-aware service offloading and migration scheme for UAV-assisted Internet of vehicles in multiaccess MEC platforms. They formulated service placement, migration, and UAV deployment as an optimization problem and utilized the Lyapunov optimization method to solve it in real time. Additionally, they introduced a multiagent deep deterministic policy gradient algorithm for near-global optimal policy determination, leveraging only local observation information to optimize serving delay, service offloading rate, and migration cost.

Wu et al. [A27] investigated participant and sample selection for efficient online FL in UAV swarms. They combined online learning with FL, enabling UAVs to supplement real-time samples and share training results, thus effectively improving ML model accuracy in unfamiliar scenes. Additionally, to reduce the training latency required to achieve expected model accuracy, their proposed algorithm allows the server UAV to select participants with high training utility, while selected client UAVs can choose more important samples. Zeng et al. [A28] proposed a novel mobility management framework for UAVs based on RL to address limited computational resources and sensing radius of UAVs. This framework periodically guides UAVs to update their decision networks collaboratively, thus well determining their movement patterns and enabling support for worst case scenarios. It adaptively makes decisions based on the current environmental context and utilizes backup UAVs to process unprocessed data when needed, thereby achieving higher cumulative payoff rewards and faster algorithmic convergence.

Considering the random characteristics of user movement and interference characteristics among different nodes, Gao et al. [A29] derived the probability of cache hit and the probability of successful transmission under different content transmission modes by using stochastic geometry methods. They utilized tiny ML to predict the request probability of user devices and then designed UAV path-planning algorithms to cover users with high request probability in a short time.

The third category of papers aims to facilitate the environmental adaptability of the Internet of UAVs. Xiong et al. [A30] proposed an object detection algorithm based on the single-stage learning framework. Their algorithm integrates adaptive feature fusion and enhances attention mechanisms to solve the object detection problem, especially for small and low-resolution objects from the perspective of UAVs. In the feature extraction phase, they utilized soft pooling to improve the feature extraction network and prevent the loss of edge information for small targets. An optimized subspace attention module is proposed to improve small object representation and reduce the impact of background noise on object detection performance.

Yang et al. [A31] proposed a UAV control framework to streamline tasks for operators in time-critical scenarios. They proposed a field-of-view transformation method by combining lightweight target detection with the UAV operator's gaze information to locate target objects, thus well-solving object detection failure caused by reflection. Additionally, they introduced the incremental proportion integration differentiation control algorithm to realize automatic real-time UAV control. To address distorted ground data distribution, Yu et al. [A32] proposed a bias-compensation augmentation learning framework to enhance semantic information extraction capability. They employed an artificially augmented neural network to determine relative bias values of collected image data and proposed a bias-compensated computational offloading strategy to address limited computation resources. Their strategy enables a tradeoff in network scheduling efficiency and model accuracy.

Fu et al. [A33] formulated a decision problem to optimize the deployment of multiple UAVs, aiming to maximize the communication coverage ratio of vehicular networks. They proposed corresponding solutions under the dual-layer nested decision-making framework, centralized training with decentralized deployment, and accelerated training by merely collecting critical states into a dense sampling buffer. Lu et al. [A34] presented a method for enhancing indoor UAV localization by integrating fine-time measurement for distance calculation and DNN for error correction. By utilizing physical-layer information, the system discerns environmental traits and appraises signal propagation paths by extracting temporal domain data from channel state information and learning nonlinear associations among delay, power, and mean ranging error.

Wang et al. [A35] proposed a Lagrangian-based proximal policy optimization algorithm to optimize the policy based on primal pairs. They optimized the user time allocation and the height of UAVs to maximize network throughput and minimize task completion time by transforming the problem into a constrained Markov decision process (MDP). Additionally, the candidate hover points of UAV are optimized based on multiagent collaborative decision making. Finally, they used a Lagrangian-based proximal policy optimization algorithm to jointly optimize the UAV height and time allocation of wearable devices. Li et al. [A36] proposed a hierarchical intelligent traffic offloading network optimization framework based on deep FL to address the severe capacity pressure of cellular networks. Through FL, the UAV swarm is organized hierarchically, and the leader UAV is selected as the top-level central server for model aggregation. Additionally, the traffic offloading problem is formalized as an MDP.

Chen et al. [A37] proposed a profit-aware cooperative offloading framework with lightweight DRL to address the performance degradation caused by dynamic system states and various traffic patterns in UAV-assisted MEC systems. First, they formulated the profit maximization problem and proved its NP-hardness. Next, they designed an improved DRL method with twin critics' networks and a delay mechanism are to resolve such issues as Q-value overestimation and high variance. Finally, they developed a multiteacher distillation mechanism with an advantage value function for the DRL model.

Zhou et al. [A38] proposed a scheme for constructing and distributing radio maps applied in UAV-assisted MEC networks. They converted the distribution of radio maps into a collaborative process between UAV servers and smart mobile devices, designing different distribution models for varying network conditions. To enhance system performance and operational efficiency, they integrated the scheme with DRL to achieve seamless coordination between UAVs and mobile devices. Khan et al. [A39] investigated UAVs equipped with tiny ML algorithms to detect road damage. Specifically, they utilized UAVs and vehicle dashboard cameras to collect data for constructing the data set and training both pure and hybrid models. They developed DL target detection models for road damage recognition and infrastructure assessment.

Yi et al. [A40] presented a UAV-assisted DNN scheme that addresses the pressing need for efficient model compression without sacrificing precision. They combined gradient-based sensitivity analysis techniques with a multilayer perceptron architecture and developed a dynamic framework capable of adapting its structure to diverse tasks while maintaining superior performance. Their approach utilizes gradient-based sensitivity analysis instead of traditional sensitivity analysis by leveraging gradient information to assess node importance within large-scale models efficiently. Kalenberg et al. [A41] proposed a scheme to maximize system robustness by integrating a millimeter-scale 64-pixel depth sensor with a low-resolution grayscale camera. Detection of nano-UAV is achieved by using a tiny ML-based convolutional neural network, followed by reorientation via a lightweight auto-navigation system. To assess its effectiveness, the authors conducted their tests in a Crazyflie 2.1-based environment.

Rahim et al. [A42] proposed a solution for UAV trajectory design in space–air–ground networks to optimize energy efficiency. Their algorithm utilizes federated DRL combined with tiny ML to optimize the flight paths of low-altitude UAVs. Their primary objective is to enhance energy efficiency and operational coverage in dynamically changing environments. By distributing learning processes across devices, they intended to minimize power consumption while collecting data from ground nodes and providing efficient data offloading to high-altitude UAVs and satellites. Chopra et al. [A43] proposed a NOMA-based resource allocation scheme for cellular ultradense networks to address the resource constraints of time-sensitive applications. They derived expressions for each user pool to compute the scheduling time fraction and a generalized expression for the user scheduling time fraction for all use cases.

We would like to thank all the authors, including those whose papers cannot be selected in this SI, reviewers, editors, and staff members of the journal for their great efforts and outstanding support. Finally, we sincerely appreciate the strong support from the Editor-in-Chief, Prof. Nei Kato of the IEEE INTERNET OF THINGS JOURNAL.

APPENDIX: RELATED ARTICLES

[A1] Y. Wu, D. Liu, Y. Tan, J. Ren, X. Chen, and H. Zhang, "A fast location-aware repair strategy for mobile grouped storage clusters," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 20885–20898, Jun. 2024, doi: 10.1109/JIOT.2024.3363868.

[A2] K. I. Qureshi, L. Wang, X. Xiong, and M. A. Lodhi, "Asynchronous federated learning for resource allocation in software defined Internet of UAVs," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 20899–20911, Jun. 2024, doi: 10.1109/JIOT.2023.3345864.

[A3] T. Zhang, D. Xu, O. Alfarraj, K. Yu, M. Guizani, and J. J. P. C. Rodrigues, "Design of tiny contrastive learning network with noise tolerance for unauthorized device identification in Internet of UAVs," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 20912–20929, Jun. 2024, doi: 10.1109/JIOT.2024.3376529.

[A4] K. T. Pauu, J. Wu, Y. Fan, Q. Pan, and M.-i.-V. Maka, "Differential privacy and blockchain-empowered decentralized graph federated learning enabled UAVs for disaster response," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 20930–20947, Jun. 2024, doi: 10.1109/JIOT.2023.3332216.

[A5] W. Wang, Y. Zhang, Q. Liu, T. Wang, and W. Jia, "Edge-intelligence-based computation offloading technology for distributed Internet of Unmanned Aerial Vehicles," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 20948–20957, Jun. 2024, doi: 10.1109/JIOT.2024.3383896.

[A6] F. Fu et al., "Incentive mechanism against bounded rationality for federated learning-enabled Internet of UAVs: A prospect theory-based approach," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 20958–20969, Jun. 2024, doi: 10.1109/JIOT.2024.3381636.

[A7] Y. Wu, L. Yang, L. Zhang, L. Nie, and L. Zheng, "Intrusion detection for Unmanned Aerial Vehicles security: A tiny machine learning model," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 20970–20982, Jun. 2024, doi: 10.1109/JIOT.2024.3360231.

[A8] R. Liu, M. Xie, A. Liu, and H. Song, "Joint optimization risk factor and energy consumption in IoT networks with TinyML-enabled Internet of UAVs," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 20983–20994, Jan. 2024, doi: 10.1109/JIOT.2023.3348837.

[A9] Z. Zhou et al., "MR-FFL: A stratified community-based mutual reliability framework for fairness-aware federated learning in heterogeneous UAV networks," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 20995–21009, Jun. 2024, doi: 10.1109/JIOT.2024.3357779.

[A10] X. Zhu et al., "Secure data transmission based on reinforcement learning and position confusion for Internet of UAVs," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21010–21020, Jun. 2024, doi: 10.1109/JIOT.2024.3368200.

[A11] J. Kang et al., "Tiny multi-agent DRL for twins migration in UAV metaverses: A multi-leader multi-follower Stackelberg game approach," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21021–21036,Jun. 2024, doi: 10.1109/JIOT.2024.3360183.
[A12] S. Zhou et al., "Transferability of adversarial attacks on tiny deep learning models for IoT Unmanned Aerial Vehicles," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21037–21045, Jun. 2024, doi: 10.1109/JIOT.2023.3329954.
[A13] J. Zheng et al., "Trust management of tiny federated learning in Internet of Unmanned Aerial Vehicles," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21046–21060, Jun. 2024, doi: 10.1109/JIOT.2024.3363443.
[A14] M. Xi et al., "A lightweight reinforcement learning-based real-time path planning method for Unmanned Aerial Vehicles," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21061–21071, Jun. 2024, doi: 10.1109/JIOT.2024.3350525.
[A15] G. Wu, F. Liu, S. Li, Q. Song, and Z. Tang, "AC-DNN: An adaptive compact DNNs architecture for collaborative learning among heterogeneous smart devices," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21072–21082, Jun. 2024, doi: 10.1109/JIOT.2024.3355175.
[A16] J. Li et al., "Centroid-guided target-driven topology control method for UAV Ad-hoc networks based on tiny deep reinforcement learning algorithm," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21083–21091, Jun. 2024, doi: 10.1109/JIOT.2024.3376647.
[A17] W. Hu et al., "Cost-effective multi-type data scheduling for blockchain in massive Internet of UAVs," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21092–21102, Jun. 2024, doi: 10.1109/JIOT.2023.3337262.
[A18] B. Jia et al., "Coverage path planning for IoUAVs with tiny machine learning in complex areas based on convex decomposition," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21103–21111, Jun. 2024, doi: 10.1109/JIOT.2024.3361857.
[A19] W. Zhang, Y. Qin, and X. Tao, "Decoding brain-controlled intention for UAVs and IVs based on lightweight network," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21112–21124, Jun. 2024, doi: 10.1109/JIOT.2024.3367690.
[A20] N. Liu et al., "Dynamic charging strategy optimization for UAV-assisted wireless rechargeable sensor networks based on deep Q-network," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21125–21134, Jun. 2024, doi: 10.1109/JIOT.2023.3345311.
[A21] X. Kong, C. Ni, G. Duan, G. Shen, Y. Yang, and S. K. Das, "Energy consumption optimization of UAV-assisted traffic monitoring scheme with tiny reinforcement learning," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21135–21145, Jun. 2024, doi: 10.1109/JIOT.2024.3365293.
[A22] C. Zhao, M. Sheng, J. Liu, T. Chu, and J. Li, "Energy- efficient power control for multiple-task split inference in UAVs: A tiny learning-based approach," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21146–21157, Jun. 2024, doi: 10.1109/JIOT.2024.3365199.
[A23] T. Zheng, Y. Qiu, Y. Zheng, Q. Wang, and X. Chen, "Enhancing TinyML-based container escape detectors with systemcall semantic association in UAVs networks," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21158–21169, Jun. 2024, doi: 10.1109/JIOT.2024.3361452.
[A24] F. Chen, P. Li, S. Pan, L. Zhong, and J. Deng, "Giant could be tiny: Efficient inference of giant models on resource- constrained UAVs," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21170–21179, Jun. 2024, doi: 10.1109/JIOT.2024.3366531.
[A25] L. Zhong, Z. Chen, H. Cheng, and J. Li, "Lightweight federated graph learning for accelerating classification inference in UAV-assisted MEC systems," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21180–21190, Jun. 2024, doi: 10.1109/JIOT.2024.3365675.
[A26] Y. Liu, P. Lin, M. Zhang, Z. Zhang, and F. R. Yu, "Mobile-aware service offloading for UAV-assisted IoVs: A multi-agent tiny distributed learning approach," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21191–21201, Jun. 2024, doi: 10.1109/JIOT.2024.3373225.
[A27] F. Wu et al., "Participant and sample selection for efficient online federated learning in UAV swarms," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21202–21214, Jun. 2024, doi: 10.1109/JIOT.2024.3363181.
[A28] H. Zeng, Z. Zhu, Y. Wang, Z. Xiang, and H. Gao, "Periodic collaboration and real-time dispatch using an actor–critic framework for UAV movement in mobile edge computing," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21215–21226, Jun. 2024, doi: 10.1109/JIOT.2024.3366506.
[A29] X. Gao, X. Wang, and Z. Qian, "Probabilistic caching strategy and TinyML-based trajectory planning in UAV- assisted cellular IoT system," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21227–21238, Jun. 2024, doi: 10.1109/JIOT.2024.3360444.
[A30] X. Xiong et al., "Adaptive feature fusion and improved attention mechanism based small object detection for UAV target tracking," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21239–21249, Jun. 2024, doi: 10.1109/JIOT.2024.3367415.
[A31] M. Yang, J. Wang, Y. Gao, and B. Hu, "Aim where you look: Eye-tracking-based UAV control framework for automatic target aiming," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21250–21260, Jun. 2024, doi: 10.1109/JIOT.2024.3390115.
[A32] T. Yu et al., "Bias-compensation augmentation learning for semantic segmentation in UAV networks," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21261–21273, Jun. 2024, doi: 10.1109/JIOT.2024.3373454.
[A33] H. Fu, J. Wang, J. Chen, P. Ren, Z. Zhang, and G. Zhao, "Dense multi-agent reinforcement learning aided multi-UAV information coverage for vehicular networks," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21274–21286, Feb. 2024, doi: 10.1109/JIOT.2024.3367005.
[A34] B. Lu, M. Wang, W. Wen, and Y. Zhang, "Improving FTM ranging accuracy based On DNN for UAV localization," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21287–21298, Jun. 2024, doi: 10.1109/JIOT.2023.3342979.
[A35] X. Wang, X. Wan, H. Ji, H. Hu, Z. Chen, and Y. Xiao, "Joint UAV deployment and user scheduling for wireless powered wearable networks," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21299–21311, Jun. 2024, doi: 10.1109/JIOT.2024.3360078.
[A36] F. Li et al., "Multi-UAV hierarchical intelligent traffic offloading network optimization based on deep federated learning," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21312–21324, Jun. 2024, doi: 10.1109/JIOT.2024.3363188.
[A37] Z. Chen, J. Zhang, X. Zheng, G. Min, J. Li, and C. Rong, "Profit-aware cooperative offloading in UAV-enabled MEC systems using lightweight deep reinforcement learning," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21325–21336, Jun. 2024, doi: 10.1109/JIOT. 2023.3331722.
[A38] L. Zhou, H. Mao, X. Deng, J. Zhang, H. Zhao, and J. Wei, "Real-time radio map construction and distribution for UAV-assisted mobile edge computing networks," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21337–21346, Jun. 2024, doi: 10.1109/JIOT.2024.3378217.
[A39] M. W. Khan et al., "Real-time road damage detection and infrastructure evaluation leveraging unmanned aerial vehicles and tiny machine learning," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21347–21358, Jun. 2024, doi: 10.1109/JIOT.2024.3385994.
[A40] L. Yi, Y. Wu, A. Tolba, T. Li, S. Ren, and J. Ding, "SA-MLP-mixer: A compact All-MLP deep neural net architecture for UAV navigation in indoor environments," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21359–21371, Jun. 2024, doi: 10.1109/JIOT.2024.3359662.
[A41] K. Kalenberg et al., "Stargate: Multimodal sensor fusion for autonomous navigation on miniaturized UAVs," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21372–21390, Jun. 2024, doi: 10.1109/JIOT.2024.3363036.
[A42] S. Rahim, L. Peng, and P.-H. Ho, "TinyFDRL-enhanced energy-efficient trajectory design for integrated space–air–ground networks," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21391–21401, Jun. 2024, doi: 10.1109/JIOT.2024.3361394.
[A43] G. Chopra, S. Rani, W. Viriyasitavat, G. Dhiman, A. Kaur, and S. Vimal, "UAV-assisted partial co-operative noma based resource allocation in C2VX and TinyML based use case scenario," *IEEE Internet Things J.*, vol. 11, no. 12, pp. 21402–21410, Jun. 2024, doi: 10.1109/JIOT.2024.3351733.

ZHAOLONG NING, *Guest Editor*
School of Communication and Information Engineering
Chongqing University of Posts and Telecommunications
Chongqing 400065, China
E-mail: z.ning@ieee.org

ABBAS JAMALIPOUR, *Guest Editor*
School of Electrical and Computer Engineering
The University of Sydney
Sydney, NSW 2006, Australia
E-mail: a.jamalipour@ieee.org

MENGCHU ZHOU, *Guest Editor*
New Jersey Institute of Technology
Newark, NJ 07102, USA
E-mail: mengchu@gmail.com

BEHROUZ JEDARI, *Guest Editor*
Department of L1 DU
Nokia Corporation
02610 Espoo, Finland
E-mail: behrouz.jedari@nokia.com

Zhaolong Ning received the Ph.D. degree from Northeastern University, Shenyang, China, in 2014.

He was a Research Fellow with Kyushu University, Fukuoka, Japan, from 2013 to 2014. He is currently a Full Professor with the School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing, China. He has published over 150 scientific papers in international journals and conferences. His research interests include mobile-edge computing, UAV networks, machine learning, and resource management.

Prof. Ning has been a Highly Cited Researcher (Web of Science) since 2020. He serves as an Associate Editor and a Guest Editor for several journals, such as IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON SOCIAL COMPUTATIONAL SYSTEMS, and IEEE INTERNET OF THINGS JOURNAL.

Abbas Jamalipour (Fellow, IEEE) received the Ph.D. degree in electrical engineering from Nagoya University, Nagoya, Japan, in 1996.

He is a Professor of Ubiquitous Mobile Networking with The University of Sydney, Sydney, NSW, Australia. He has authored nine technical books, 11 book chapters, over 550 technical papers, and five patents, all in the area of wireless communications and networking.

Prof. Jamalipour was a recipient of the number of prestigious awards, such as the 2019 IEEE ComSoc Distinguished Technical Achievement Award in Green Communications, the 2016 IEEE ComSoc Distinguished Technical Achievement Award in Communications Switching and Routing, the 2010 IEEE ComSoc Harold Sobol Award, the 2006 IEEE ComSoc Best Tutorial Paper Award, and over 15 best paper awards. He has been the General Chair and the Technical Program Chair of several prestigious conferences, including IEEE ICC, GLOBECOM, WCNC, and PIMRC. He was the President of the IEEE Vehicular Technology Society from 2020 to 2021. Previously, he held the positions of the Executive Vice-President and the Editor-in-Chief of VTS Mobile World. He was the Vice President-Conferences and a member of Board of Governors of the IEEE Communications Society. He is a member of Advisory Board of IEEE INTERNET OF THINGS JOURNAL. Since January 2022, he has been the Editor-in-Chief of IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY. He was also the Editor-in-Chief of IEEE WIRELESS COMMUNICATIONS. He has been an Elected Member of the Board of Governors of the IEEE Vehicular Technology Society since 2014. He is a Fellow of the Institute of Electrical, Information, and Communication Engineers and the Institution of Engineers Australia, an ACM Professional Member, and an IEEE Distinguished Speaker.

MengChu Zhou (Fellow, IEEE) received the Ph.D. degree in computer and systems engineering from Rensselaer Polytechnic Institute, Troy, NY, USA, in 1990.

He joined New Jersey Institute of Technology, Newark, NJ, USA, in 1990, where he is a Distinguished Professor of Electrical and Computer Engineering and the Director of Discrete-Event Systems Laboratory. He has authored or coauthored 1200 publications, including 17 books, more than 850 journal papers (more than 650 in IEEE Transactions), and 32 book chapters, and holds 31 patents and several pending ones. He recently coauthored books include *Learning Automata and their Applications to Intelligent Systems* (IEEE Press/Wiley, Hoboken, NJ, 2024, with J. Zhang), *Device-Edge-Cloud Continuum Paradigms, Architectures and Applications* (Springer Nature, 2023, with C. Savaglio, G. Fortino, and J. Ma), and *Sustainable Manufacturing Systems: An Energy Perspective* (IEEE Press/Wiley, Hoboken, Hoboken, NJ, 2022, with L. Li). His research interests include intelligent automation, Petri nets, Internet of Things, big data, cloud/edge computing, transportation, and energy systems.

Dr. Zhou was the Founding Editor of the IEEE Press Book Series on Systems Science and Engineering and the Editor-in-Chief of the IEEE/CAA JOURNAL OF AUTOMATICA SINICA. He is the Founding Chair/Co-Chair of Technical Committee on AI-Based Smart Manufacturing Systems of IEEE Systems, Man, and Cybernetics Society, Technical Committee on Semiconductor Manufacturing Automation, and Technical Committee on Digital Manufacturing and Human-Centered Automation of the IEEE Robotics and Automation Society. He is a Fellow of the International Federation of Automatic Control, American Association for the Advancement of Science, Chinese Association of Automation, and National Academy of Inventors.

Behrouz Jedari received the B.Sc. and M.Sc. degrees in software engineering from Islamic Azad University, Tehran, Iran, in 2006 and 2009, respectively, and the Ph.D. degree in computer science from Dalian University of Technology, Dalian, China, in 2017.

He was a Postdoctoral Researcher with the Department of Computer Science, Aalto University, Espoo, Finland. He is currently a Research and Development Software Engineer for 4G/5G L1 technologies with Nokia, Espoo. His research interests include network optimization, resource allocation, and network economics.