AI Driven Heterogeneous MEC System for Dynamic Environment - Challenges and Solutions

Feibo Jiang, Kezhi Wang, Li Dong, Cunhua Pan, Wei Xu, and Kun Yang.

Abstract—By taking full advantage of Computing, Communication and Caching (3C) resources at the network edge, Mobile Edge Computing (MEC) is envisioned as one of the key enablers for the next generation network and services. However, current fixed-location MEC architecture may not be able to make real-time decision in dynamic environment, especially in large-scale scenarios. To address this issue, in this paper, a Heterogeneous MEC (H-MEC) architecture is proposed, which is composed of fixed unit, i.e., Ground Stations (GSs) as well as moving nodes, i.e., Ground Vehicles (GVs) and Unmanned Aerial Vehicles (UAVs), all with 3C resource enabled. The key challenges in H-MEC, e.g., mobile edge node management, real-time decision making, user association and resource allocation along with the possible Artificial Intelligence (AI)-based solutions are discussed in this paper. In addition, an AI-based joint Resource scheduling (ARE) framework is proposed, with simulation results shown to verify the efficiency of our proposed framework.

Index Terms—Heterogeneous mobile edge computing, artificial intelligence, deep neural network, dynamic environment.

I. INTRODUCTION

Recently, with the increasing popularity of new resource-intensive applications, e.g., Augmented Reality (AR) and Virtual Reality (VR), the quality of our life is expected to be improved significantly. With the emerging mobile Internet, there is a growing trend to execute the above attractive applications in our User Equipments (UEs), e.g., mobile phones and handheld devices. This trend motivates the fast development of smart UEs equipped with intelligent functions that require higher computation resources. However, this contradicts to the sizes and the battery capacities of the UEs.

Fortunately, Mobile Edge Computing (MEC) (1) has been proposed by taking full advantage of cooperation between Communication, Computation and Caching (3C) resources at the network edge. Specifically, MEC can enable UEs with computational intensive tasks to offload them to the edge cloud and is envisioned as one of the key enabling technologies for the next generation mobile networks (2).

Feibo Jiang (jiangfb@hunnu.edu.cn) is with Hunan Provincial Key Laboratory of Intelligent Computing and Language Information Processing, Hunan Normal University, Changsha, China, Kezhi Wang (kezhi.wang@northumbria.ac.uk) is with the department of Computer and Information Sciences, Northumbria University, UK, Li Dong (Dlj2017@hunnu.edu.cn) is with Key Laboratory of Hunan Province for New Retail Virtual Reality Technology, Hunan University of Commerce, Changsha, China, Cunhua Pan (Email: c.pan@qmul.ac.uk) is with School of Electronic Engineering and Computer Science, Queen Mary University of London, London, E1 4NS, UK, Wei Xu (wxu@seu.edu.cn) is with NCRL, Southeast University, Nanjing, China, Kun Yang (kunyang@essex.ac.uk) is with the School of Computer Sciences and Electrical Engineering, University of Essex, CO4 3SQ, Colchester, UK and also with University of Electronic Science and Technology of China, Chengdu, China.

However, the traditional MEC architecture is fixed, which makes them difficult to be applied in the next generation networks, which are not only expected to accommodate an unprecedented dynamic and heterogeneous environment, but also have the capacity to support on-demand hotspot areas and temporary activities, in a fast and highly reliable manner. In other words, in the future, we envision more flexible user patterns and services, i.e., the number, the locations and the service requirement of the mobile users may be constantly changing, which makes the current fixed MEC architecture difficult to be applied.

To address the above-mentioned problem, in this paper, we propose a Heterogeneous MEC (H-MEC) system, which is composed of fixed Ground Stations (GSs), mobile Unmanned Aerial Vehicles (UAVs) and Ground Vehicles (GVs), all equipped with 3C resources. H-MEC is more flexible than the traditional MEC system and is more suitable in dynamic environment, as UAVs can GSs can be deployed per request. However, various research challenges arise when applying H-MEC in dynamic environment, such as mobile edge node management, real-time decision making, fast user association and resource allocation. In this paper, we will summarize the key challenges in deploying H-MEC in dynamic environment and propose Artificial Intelligence (AI)-based solutions to tackle these issues. The contributions of this paper are summarized as follows:

(1) We first discuss an AI driven H-MEC architecture and then summarize the typical applications of this architecture.

(2) Next, we show the key challenges of H-MEC applied in dynamic environment, i.e., in the scenarios where the number, the locations and the requirement of the UEs are constantly changing. Moreover, we show possible AI-based solutions to address the above challenges.

(3) Finally, we give an AI-based joint Resource scheduling (ARE) framework and also show how ARE can be applied in dynamic environment, as a case study. Simulation results are also provided to verify the effectiveness of our proposed framework.

II. AI DRIVEN H-MEC ARCHITECTURE

In this section, we give an AI driven H-MEC architecture in Fig. (1) In H-MEC, we assume there is the central cloud which can not only provide centralized 3C capacities for signal processing related tasks (e.g., fast Fourier transformation, encoding and decoding), but also provide resource for service related tasks (e.g., AI model training and inference), due to its powerful accumulated processing capacities. In addition, we
assume there are a number of distributed edge clouds served by both fixed nodes (i.e., GSs) and mobile nodes (i.e., UAVs and GVs). Similar to the central cloud, the GSs, UAVs and GVs are all equipped with 3C resources. UAVs and GVs, due to their feature of flexibility, can be deployed swiftly on demand. In general, UAV moves much faster than GV, but with less 3C resources. GV moves slower but hold more resource and also it normally has more energy on board, compared to UAV. GS has the most available resource but it is a fixed architecture. In addition, as UAVs can fly close to the user and therefore they can provide very low-latency communication and services. Due to 3C resources available in H-MEC, AI based models can be trained in both centralized cloud and edge nodes but with different accuracy and abilities, due to their available resource. Some complex model can be trained in the place with more resources, e.g., centralized cloud server and then downloaded to the places with less resource, e.g., UAVs. Also, inference can be made in either cloud server or edge nodes, depending on the latency requirement of the applications or users. The feature of different H-MEC components are summarised in Table I.

The proposed H-MEC architecture is particularly useful in the following scenarios:

1. Temporary application: For instance, in a public event or a football match where there are a large number of people gathered. They may be interested in recording and exchanging high quality video contents. In these scenarios, it is very likely to have a large amount of traffic generated, particularly during the intervals of main events in the stadium.

2. Unexpected application: For example, in the traffic jam, users inside the cars or buses would like to have data services using their mobile devices. Moreover, the traffic coordination center may also need to communicate with the road units and cars so as to restore the traffic. This may create a large amount of data traffic, which may need the assistance of MECs.

3. Critical application: For instance, in an emergency situation or natural disaster where an earthquake occurs and people try to contact their relatives. Moreover, the rescue crews may need VR device to guide them to the place where needed. Those VR devices may need a large amount of computing resource. Therefore, the mobile edge nodes can be deployed to provide 3C resources.

III. RESEARCH CHALLENGES

Although H-MEC architecture has many benefits to be applied in dynamic scenarios as discussed before, the mobility

TABLE I: Comparison for different H-MEC components.

| Components     | Cloud       | GS    | GV    | UAV    |
|----------------|-------------|-------|-------|--------|
| 3C Resource    | Very Large  | Large | Small | Very Small |
| Mobility       | None        | None  | Slow  | Fast   |
| Serving Time   | Unlimited   | Unlimited | Long | Short   |
| Deployment     | Fixed       | Fixed | 2D and restricted | 3D |
| Response Time  | Long        | Long  | Short | Short   |
| AI Model       | Very Complex | Complex | Simple | Simple   |
| AI Modal Training | Offline   | Incremental | Incremental | None |
| Data Collection | No         | Yes   | Yes   | Yes    |
| Data Type      | Global      | Local | Local | Local   |
of mobile nodes, e.g. UEs and MECs make the network topology highly unstable, which bring significant challenges as follows:

1. Mobile edge node deployment: It is challenging to determine where to deploy the mobile edge nodes in dynamic environment, as the new edge servers joining the networks may lead to user offloading the tasks to them and then generate interference to the existing environment. Also, the mobile nodes, e.g., UAVs that are normally resource constrained may be difficult to meet the requirement of applications or users if lack of proper predictions. Dynamic programming can be used to calculate the optimal mobile edge node deployment. However, this method can only provide a snapshot of the optimal or sub-optimal solutions but fail to consider the correlation between different users in continuous time.

2. Real-time decision making: The diverse requirements of different applications, time-varying content request, and the mobility of UEs make real-time decision a very challenging task. It is time-consuming for traditional convex optimization based methods, e.g., coordinate descent method. To address this problem, as convex optimization based methods often require considerable number of iterations to reach a satisfactorily locally optimal solution. Moreover, convex optimization based methods may not be suitable for dynamic environment, as the optimization problem needs to be re-solved once the requirements or user patterns vary.

3. Large-scale user associations: The typical use case of H-MEC, such as stadium or open air festival, may need to support massive UEs and applications. This problem normally include integer variables and is NP-hard. Traditional solution was to apply the convex-based solutions or evolutionary algorithms. However, these solutions suffer from high complexity and are time-consuming. Moreover, branch and bound algorithm may be applied here but the search space of this method increases exponentially with the number of users and are computationally prohibitive.

4. Resource management under specific constraints: In H-MEC, edge nodes can be served by mobile units, e.g., GV s and UAVs and they are normally resource-constrained. The coverage of mobile nodes, e.g., UAV may also be limited, as the communications links can be blocked by buildings. In addition, battery capacities cloud limit the capacity of mobile edge nodes as well. Therefore, all the above constraints need to be tackled jointly and properly, which create big challenges. Several AI based solutions, such as neural networks based method are recently proposed by researchers but they are generally not good at dealing with the constraints.

5. Caching deployment optimization: Caching has been identified as an important aspect by bringing storage functionality to edge servers. Deciding where/how/what to cache appropriate content have a profound effect on Quality of Service (QoS) requirement of UEs. Different from static MEC architecture, mobile edge nodes can be deployed on demand via tracking the mobility pattern of users and avoiding frequently updating the content from the core network. How to predict mobility patterns and content request information of users remains the main challenges.

6. Security and privacy issues: This is critical for H-MEC systems, as the mobile edge nodes might not be able to detect an attack due to the lack of global information of the whole networks. Moreover, classical attack detection methods normally need manual feature engineering (e.g., feature design, selection and extraction) and therefore is hard to be implemented in dynamic environment. Thus, new approaches are highly required.

IV. AI-BASED SOLUTIONS IN H-MEC

To address the above-mentioned challenges, in this section, we first discuss the AI-based solutions, which are well-known for its excellent modelling and prediction abilities. Then, we will give some tips in applying these solutions.

A. AI-based solutions

1. To deploy mobile edge nodes effectively and automatically, an unsupervised learning algorithm (e.g., the clustering algorithm) may be applied to analyse the locations, behaviours and preferences of UEs. Fuzzy C-Means (FCM) clustering is an improvement of common clustering algorithm, which adopts a soft fuzzy partition instead of the traditional rigid data classification, and thus could be applied to determine the dynamic deployment of mobile edge nodes. Another idea of deploying edge node could be to use the deep reinforcement learning method (e.g., Deep Deterministic Policy Gradient, DDPG), which can learn optimal placement policies by considering the coverage, energy consumption and connectivity of edge nodes in the reward function, and place the mobile nodes intelligently.

2. To address the real-time decision-making problem, Deep Neural Networks (DNN) could be applied as the real-time decision-making model due to the fact that once the training of DNN is completed, decisions can be made very fast by applying only a few simple algebra calculations. Moreover, by increasing the diversity of samples, DNN model is not sensitive to the dynamic environment. In addition, Recurrent Neural Networks (RNN) could be applied as well, due to its outstanding prediction and reasoning capabilities in real time. The Gated Recurrent Unit (GRU) network, which is a novel RNN, can make each recurrent unit to adaptively capture dependencies of different time scales. Also, the GRU simplifies the structure of RNNs by introducing reset and update gates, which can exploit the semantics and contexts from the input data (e.g., the changing channel quality information, CQI). For instance, H-MECs can apply the fast fading CQI to activate the reset gates and use the long-term large-scale channel fading information to activate the update gates and then make the real-time decision making fully viable.

3. To solve large-scale user association problems, Convolutional Neural Networks (CNNs) may be applied, due to its excellent feature extraction abilities. For instance, in H-MEC, CNN can be applied to identify important features (e.g., users’ behaviours, channel quality) from the original large-scale information by applying several convolutional layers and then reduce the dimensionality of the original problem. To this end, the complexity of primal large-scale problem may be significantly reduced based on the extracted features.
### TABLE II: Typical AI-based solutions in H-MEC.

| AI-based solutions       | Algorithm     | Advantages                                                                 | Disadvantages                                                                 |
|--------------------------|---------------|----------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| Supervised learning      | GRU, bi-LSTM  | Outstanding memory attribute and time series prediction ability.           | • Labeled training data requirement.                                         |
|                          |               |                                                                           | • Unable to handle the constraint problems.                                   |
|                          |               |                                                                           | • Model is sophisticated and hard to deploy on the mobile equipment.          |
|                          | CNN           | Mature technology and high recognition accuracy.                          |                                                                               |
| Unsupervised learning    | FCM           | Soft clustering and no labeled sample requirement.                        | The solution is just an approximate version of the optimal result and rely on initial data distribution. |
|                          | SAE           | Feature learning automatically and no labeled sample requirement.         |                                                                               |
| Reinforcement learning   | DDPG          | Learning from the environment and no labeled sample requirement.          | The final results can be unstable and hard to reproduce [6].                  |

Another idea of solving the large-scale network optimization is to apply clustering algorithm, which divides original variables into several clusters. In this way, the original optimizations can be divided into several small-scale sub-problems and tackled efficiently [10].

(4) For the resource management problems with several constraints, as mentioned before, it is difficult for AI-based solutions to address them. This is because, AI-based solutions, e.g., neural networks, are normally designed for optimizations without constraints and therefore the output of neural networks may not strictly satisfy all constraints. In this case, other methods, e.g., extra check may be conducted. Moreover, another layer may be attached to the networks dedicated to the feasibility check.

(5) For caching deployment in H-MEC, the bidirectional Long Short Term Memory (bi-LSTM) network [11] could be applied, as it can exploit both the previous and future contexts by analysing the data (e.g., video recoding clips) from two reverse directions. In particular, this scheme can deploy cache by considering the requested information at its previous and future states and predict the content request distribution. In the proposed H-MEC, bi-LSTM can be implemented to allow both fixed and mobile edge nodes to update their local content cache according to the mobility patterns of users while avoiding frequent access to the core network.

(6) For security and privacy issues in H-MEC, one may notice that the main obstacle of learning based methods lies in lack of samples. In other words, automatic feature selection and extraction are highly required. Auto-encoder algorithm may be applied. For example, H-MEC could benefit from a pre-training scheme of Stacked Auto-Encoder (SAE) [12] for automatic feature learning. In particular, SAE can be applied to train an attack detection model with a mix of unlabelled normal/attack samples so that the model identifies patterns of attack and normal data by an auto-encoder scheme, this can in turn improve the accuracy of the attack detection model on unseen and mutated attacks.

Moreover, in Table II we summarize the main advantages and disadvantages of different AI-based solutions in H-MEC.

B. Tips

In this subsection, we will give some tips on the design of DNN-based solutions (e.g., CNN, GRU, bi-LSTM, SAE and DDPG), as the typical representatives of AI-based methods applied in H-MEC.

1) Incremental learning: When applying DNN in H-MEC, one may need to continually train and adjust the parameters in response to the fast changing environment. Incremental learning could be applied here to update the DNN model dynamically. In H-MEC, edge servers can track the variations of the environment and update the training data periodically and applied to re-train the learning model to guarantee that the model performs well even when the environment is constantly changing.

2) Compressing learning: As the mobile edge nodes are resource/energy constrained, it is important to reduce the energy and computation consumption during the leaning process. Therefore, the compressing learning could be applied. Compressing learning can reduce parameters of DNNs while mitigating result accuracy loss. Since DNNs are usually extremely over parameterized, they are capable of compression. Several approaches have been proposed to facilitate this process, such as network pruning, knowledge distillation, weight quantification and lossless compression [13].

3) Experience Learning: In H-MEC, it is important to get the high-quality data as training samples, otherwise, the trained model may be biased. To achieve this goal, experience learning may be applied here to find the optimal solutions from the historical experience data [10].

V. AI-BASED JOINT RESOURCE SCHEDULING (ARE) FRAMEWORK

In this section, we will introduce the AI-based joint Resource schEduling (ARE) framework to show the potential of AI-based solutions in H-MEC when applying it to dynamic environment.

A. Problem Formulation

We assume that there are a number of UEs and several 3C resource enhanced edge nodes, i.e., UAVs, GVs and GSs,
as shown in Fig. 1. The locations of GSs are assumed to be fixed while the locations of GV s and UAVs can be optimized. We assume each UE has a computation task, which can be executed either locally or by one of the edge nodes. We also assume UAVs have limited coverage, which depends on the angle of the antennas installed on UAVs. Also, we assume each task has the QoS requirement, meaning that the task has to be completed in the required amount of the time. The computing resource is also assumed to be limited in each edge nodes.

We aim to obtain an online algorithm to minimize the energy consumption of all the UEs, by jointly optimizing the deployment of GV s and UAVs, user association and resource allocation in real time, while considering dynamic environment, i.e., the number and the locations of UEs may vary. Therefore, one can formulate the optimization problem as follows:

- **Objective function:** the minimization of total energy consumption of all the UEs (i.e., the transmitted energy consumption if offloading the tasks or the local execution energy consumption if executing the tasks locally);
- **Decision variables:** user association, resource allocation and the locations of GV s and UAVs;
- **Constraint C1:** the coverage of each UAV;
- **Constraint C2:** the QoS requirement of each task;
- **Constraint C3:** the computing resource available in each edge node (i.e., GSs, GV s and UAVs).

One can see that the above problem is a mixed integer non-linear programming (MINLP), which is very hard to address. This is because the user association is binary whereas the resource allocation is continuous. Also, the location variables of UAVs and GV s are continuous as well. Furthermore, there are other major difficulties as follows:

1. This is a large-scale optimization problem as we consider the scenario where there is a large number of UEs;
2. Real-time decision-making is required;
3. We assume it is in dynamic environment, which means the parameters, e.g., the channel state information, the locations of UEs may change. Next, we introduce our proposed ARE framework.

### B. ARE framework

To address the above problem, we propose a novel ARE framework, as shown in Fig. 2, which includes the offline training and online decision-making stages.

1. **Overview:**

    **Offline training phase:** The training phase can be carried out in the cloud as it holds large amount of computational and storage resources. Firstly, a Large-Scale path-loss Fuzzy C-Means (LS-FCM) algorithm (in Section-V. B. 2) is presented to predict the optimal positions of GV s and UAVs. Secondly, the U-Generation algorithm (in Section-V. B. 3) is introduced to calculate the fuzzy membership information matrix \( U \) including the small-scale fading effect and the mutual interference among the UEs. Thirdly, a U-based Particle Swarm Optimization (U-PSO) algorithm (in Section-V. B. 4) is proposed to solve the MINLP problems according to the historical data and obtain the user association and resource allocation solutions. The U-PSO will be carried out repeatedly until sufficient samples of DNN are collected. Finally, the supervised learning algorithm is used to train the DNN until the evaluation conditions are satisfactory. Note that fuzzy membership information will be served as input to the DNN, as it can provide a concise representation of the relationship between UEs and edge nodes.

    **Online decision-making phase:** The trained DNN can be implemented for online decision making. To do this, the fuzzy membership information of each UE will be input to the network and obtain the solutions, with only some simple algebraic calculations instead of solving the original optimization problem. Note that we attach a scheduling layer to DNN (in Section-V. B. 5) to guarantee the output solutions can meet the practical constrains. In addition, during the online stage, some results output by the DNN can be resolved by U-PSO as new samples and can be fed back to the DNN for the incremental learning according to the changing environment.

    In the following, we describe more details of each component of the ARE framework.

2. **LS-FCM:** Traditional FCM [7] cannot be directly used in H-MEC to obtain the required position of UAVs and GV s, as there are some fixed points in H-MEC, i.e., the positions of GSs. Moreover, the traditional FCM normally considers the distances between UEs and MECs, instead of considering Channel Quality Information (CQI) between them. Therefore, LS-FCM is proposed with two improvements. Firstly, we fix some cluster centres (i.e., GS positions) and does not allow them to participate in the iterative process. Secondly, we introduce the large-scale path-loss coefficients, instead of the distance during the iterative process in LS-FCM. Then, the positions of UAVs and GSs will be decided.

3. **U-Generation:** U-Generation is used to calculate the fuzzy membership matrix \( U \) of all the UEs, which captures small-scale fading and mutual interference between UEs by updating the membership equation which includes these information. In other words, fuzzy membership information can describe the relationship between UEs and edge nodes succinctly and then can be a perfect input of DNNs. Note that each time, we only input the fuzzy membership information of one UE to the DNN, which will be suitable for the scenarios where the number of UEs is varying and avoid the curse of dimensionality in DNN.

4. **U-PSO:** U-PSO is used to solve the proposed MINLP problem and generate high-quality samples for DNNs. Directly applying traditional PSO algorithm [15] has two drawbacks: (1) there is no procedure to check the constraints; (2) traditional PSO initializes the particle population randomly and it does not take advantage of the CQI information. To address these issues, we propose a novel U-PSO algorithm with two improvements: Firstly, we add a constraint check process to evaluate each particle. Secondly, we apply U-based roulette wheel selection strategy to provide high-quality initial solutions of PSO for accelerating convergence.

5. **DNN with scheduling layer:** We attach an additional scheduling layer to DNN for checking the constraints of the problem, as shown in the top part of Fig. 2, which includes a constraint layer and a decision layer. If the solution from
output layer is feasible, the constraint layer outputs 1 to the next layer, otherwise 0. The node in decision layer is labelled as $\Pi$, indicating that they play the role of a simple multiplier. If the solution from output layer does not satisfy the constraints, the final decision will be 0, which means UE executes the task locally.

C. Simulation Results

In the simulation, we assume that there are 100 UEs in a $100 \times 100$ m zone, with the coordinate of GS as (50 m, 50 m). The bandwidth is 1MHz, the computational capability of UE, UAV, GV and GS is set to $10^9$ cycles/s, $10^{10}$ cycles/s, $10^{11}$ cycles/s and $10^{12}$ cycles/s, respectively. The input data size, required computational capability of the task is set to 100 kB and $10^9$ cycles/s, respectively. The iteration number of LS-FCM is set to 100. The population size and iteration number of U-PSO are set to 10 and 100. The learning rate and iteration number of DNN are set to 0.4 and 500. Other parameter settings can be refereed to our companion journal version [14].

The performance of the DNN is shown in Fig. 3 (a) and (b) where in Fig. 3 (a), we plot the training loss and testing loss. It is shown that the testing loss declines sharply and stabilizes at around 0.09 when epoch is above 300, while the training loss stabilizes at around 0.08, whose value is less than the testing loss curve. In Fig. 3 (b), we further study the error distribution of all samples for the DNN. We see that 70% of the training errors are less than 0.025 and the maximum error is less than 0.4624. The same situation is observed form the error distribution of the testing samples. The simulation results verify that the proposed DNN can rapidly converge.

Finally, we compare the average energy consumption versus the number of device, as shown in Fig. 4 (a). One can see that compared to PSO, Greedy algorithm, Random research and Local executing strategies, our proposed method achieves similar performance to PSO algorithm but much better than the other algorithms. Moreover, from Fig. 4 (b), one can see that our proposed algorithm requires substantially less CPU time.

VI. CONCLUSIONS

In this paper, we have studied an AI driven H-MEC architecture, which is expected to be applied in dynamic environment. We have discussed the key challenges of the H-MEC architecture and the possible AI-based solutions. Moreover, we provide an ARE framework to show how to apply AI-based solutions in H-MEC. Simulation results were provided to show the effectiveness of our proposed framework.
Fig. 3: Performance of DNN: (a) The testing loss and training loss of DNN. (b) The training and testing error distribution of all samples for the DNN.

Fig. 4: Simulation results of our ARE framework: (a) the comparison of average energy consumption as the number of devices varies from 10 to 100. (b) the comparison of runtime between PSO and the proposed method as the number of devices varies from 10 to 100.

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