Extensive Edge Intelligence for Future Vehicular Networks in 6G

Weijing Qi, Qian Li, Qingyang Song, Lei Guo, and Abbas Jamalipour

Abstract

The 6th generation mobile network (6G) is expected to achieve a fully connected world. As a key enabling technology in 6G, edge intelligence (EI) combines artificial intelligence (AI) with mobile edge computing (MEC), further releasing the potential of edge-side data. However, edge resources from roadside units (RSUs) and base stations are insufficient to match the wide variety of services in future vehicular networks. Extensive EI with auxiliary edge resources from parked vehicles is therefore introduced in this article. To achieve the coordination between extensive edge resources and EI-assisted services for vehicular networks in 6G, we propose an intelligent service-oriented edge resource management architecture, which makes full use of knowledge extracted from a large amount of sensory data in vehicular networks. As a case study, a prediction-based edge resource activation method under this architecture is proposed, where resources of parked vehicles are activated based on the predicted user density. Simulation results demonstrate that our prediction model has high accuracy and the prediction-based resource activation approach can reduce deployment cost.

Introduction

The 6th generation mobile network (6G) is expected to achieve a fully connected world through a heterogeneous network supporting space-air-ground, and maritime and underwater communications. With artificial intelligence (AI) technology, network entities in 6G can perceive and analyze multi-dimensional data to facilitate seamless connectivity among ground devices and onboard facilities. The autonomous management capability of 6G systems is enhanced to satisfy various application requirements, such as mobile broad bandwidth and low latency (MBBLL), massive broad-bandwidth machine-type (mBBMT), and massive low-latency machine-type (mLLMT) communications, adaptively [1].

The deep integration of 6G and vehicular networks spawns future vehicular networks that have the potential to support autonomous driving and other advanced vehicular applications. A wide range of spectrum, including microwave, millimeter wave, Terahertz (THz) wave, and visible light, is used for transmitting data generated from many types of on-board sensors. Advanced intelligent vehicular applications are envisioned in the forthcoming 6G era, for instance, intelligent road environment perception, intelligent decision making, vehicle behavior controlling, and human-vehicle interactions based on Virtual Reality (VR)/Augmented Reality (AR)/Mixed Reality (MR). Powerful computing processing capability, huge storage space, and robust security guarantee of a future vehicular system are essential to satisfy the low-latency, high-reliability, and high-scalability requirements of these applications. A future vehicular network in 6G is as shown in Fig. 1.

Mobile edge computing (MEC) technology, which is widely used in the 5th generation mobile network (5G) era, can pull computing, caching, and communication (3C) resources close to end users. As a key enabling technology in 6G, edge intelligence (EI) [2] combines AI with MEC through integrating intelligent processing modules in edge network entities, further releasing the potential of vehicular data generated at the edge. Efficient service migration in highly dynamic mobile networks is explored in [3], which provides academic support for implementing intelligent vehicular applications with EI.

However, the edge resources expected to be deployed for 5G are insufficient to match the wide variety of services in EI-enabled vehicular networks in the 6G era, which need significant resources for performing AI training and inference. In particular, in those areas with dense traffic and numerous service requests, it is even more challenging to guarantee the quality of experience (QoE) and quality of service (QoS). Due to the limited coverage of base stations, frequent signal losses caused by obstructions from buildings, and huge investments to construct dedicated roadside units (RSUs), researchers are eager to find new alternatives that can provide cheaper and extensive resources, to reduce dependency on ground infrastructures.

Fortunately, researchers have observed that there is a large amount of idle 3C resources available from parked vehicles in the urban city. Generally, private vehicles spend most of the time in parking lots with their resources in idle states, where outdoor parking spaces take a large proportion. Utilizing the resources from parked vehicles in the outdoor or roadside parking spaces is a practical approach to fill the edge resource gap. Parked vehicles may consume energy for providing services to other vehicles, and a dis-

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count in parking fees can be an incentive to a parked vehicle. In this way, a 3C resource pool with a wide range of coverage can be built to serve future smart vehicles. Nevertheless, since parked vehicles possess different characteristics from ground infrastructure, activating them as auxiliary edge nodes makes the large-scale, highly dynamic, and heterogeneous network even more complicated. To achieve tight coordination of resource allocation and service provisioning with a high resource utilization rate at edge nodes, the activation and management of edge resources still face many challenges. On one hand, compared with base stations and RSUs, parked vehicles have weaker payload capacities, which results in fewer resources available at them. The tremendous variation of density and individual capability of edge nodes lead to the uneven distribution of edge resources. Edge services being implemented locally hinder resource sharing. On the other hand, traffic flows change over time and space, reflecting the varying number of service requests from vehicular users. The high-speed mobility of vehicles further triggers the spatial migration of service requests. It is crucial for vehicular networks to have rapid response, proactive exploration, and adaptive capabilities to optimize resource allocation. As a result, traditional reactive vehicular network resource management lacking intelligence can no longer satisfy the new key performance indicators (KPIs) of the future intelligent vehicular network, leading to the underutilization of resources.

In this work, we take parked vehicles as auxiliary edge nodes to provide extensive resources for implementing EI-enabled solutions for future vehicular networks in 6G, together with ground infrastructures. The idea will be abbreviated as extensive EI. To satisfy the QoS requirements of advanced vehicular applications in the 6G era, we propose an intelligent service-oriented edge resource management architecture. By making full use of knowledge such as traffic patterns extracted from a large amount of high-dimensional data in complex vehicular networks, the intelligent coordination between resources and services can be achieved. As a case study of intelligent resource management under the proposed architecture, a prediction-based edge resource activation method is designed. It adopts a convolutional long short-term memory (Conv_LSTM) model to predict user density, based on which the resources of parked vehicles are activated unevenly, to meet the high-reliability and low-latency requirements. Simulation results demonstrate that our prediction model has high accuracy and our prediction-based resource activation approach is capable of reducing deployment cost.

Potential and Challenges of Parked Vehicles Participating in EI

With the good characteristics mentioned above, parked vehicles are drawing increasing attention in edge computing. Many works consider them as service nodes to assist communications, caching, and computing. The 3C edge resources can be further endowed with intelligence capabilities to be involved in performing EI, though it is challenging. Here are related works on utilizing resources from parked vehicles and our analysis on the challenges of making parked vehicles assisting EI.

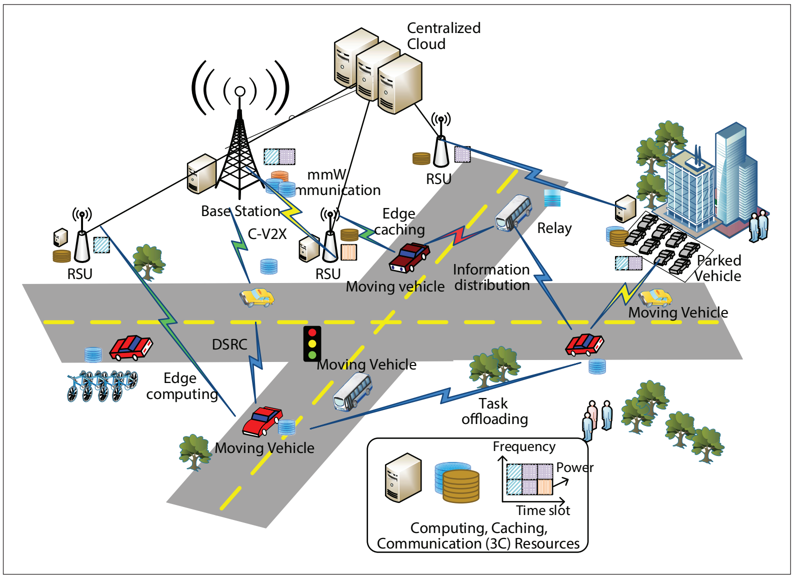

FIGURE 1. Future vehicular network in 6G.

Potential

Parked vehicles in urban areas present themselves as compelling candidates of additionally available RSUs. One of the most significant reasons is that they do not move. The incentive compatibility and individual rationality of vehicles are considered in [4], which is an instructive work to incentivize parked vehicles to participate in edge computing. Taking these roadside and outdoor parked vehicles as relay nodes and utilizing their communication resources can improve network capacity and solve the network connection problem caused by low moving vehicle density [5]. A good parking clustering management scheme such as ParkCast [6] can increase communication opportunities between parked vehicles and mobile vehicles. A parking-area-assisted routing protocol [6] is useful for emergency data transmission in urban VANETs with low-density traffic.

The idle computing and caching resources of parked vehicles are also utilized to provide edge services. For example, parked vehicle edge computing (PVEC) [7, 8] is proposed for distributed task execution. A collection of essential topics is widely studied in PVEC, including secure communication protocols between parked vehicles and edge servers [7], task assignment methods for reducing overall user cost [9], and so forth. Additionally, researchers suggest parked vehicles act as RSUs or share the processing load of RSUs. Specifically, each parked vehicle can create a coverage map based on the received signal strength and decide whether to act as an RSU [10]. A feasibility study and cost-benefit analysis verified that a small number of parked vehicles being activated as RSUs could achieve good coverage in the city. To provide high-quality information services, caching content in parked vehicles in advance is suggested [11]. An interactive model between RSUs, parked vehicles, and mobile vehicles can describe a network scenario where RSUs and parked vehicles can simultaneously provide content for mobile vehicles.

Memory footprint indicates the cache requirements for the edge tasks. Spectrum indicates the communication resource requirements for transmitting data. For a specific application, there are determinate minimum ALEMS requirements. To satisfy these requirements, it is necessary to select edge entities that can provide enough residual resources with sufficient EI capability.

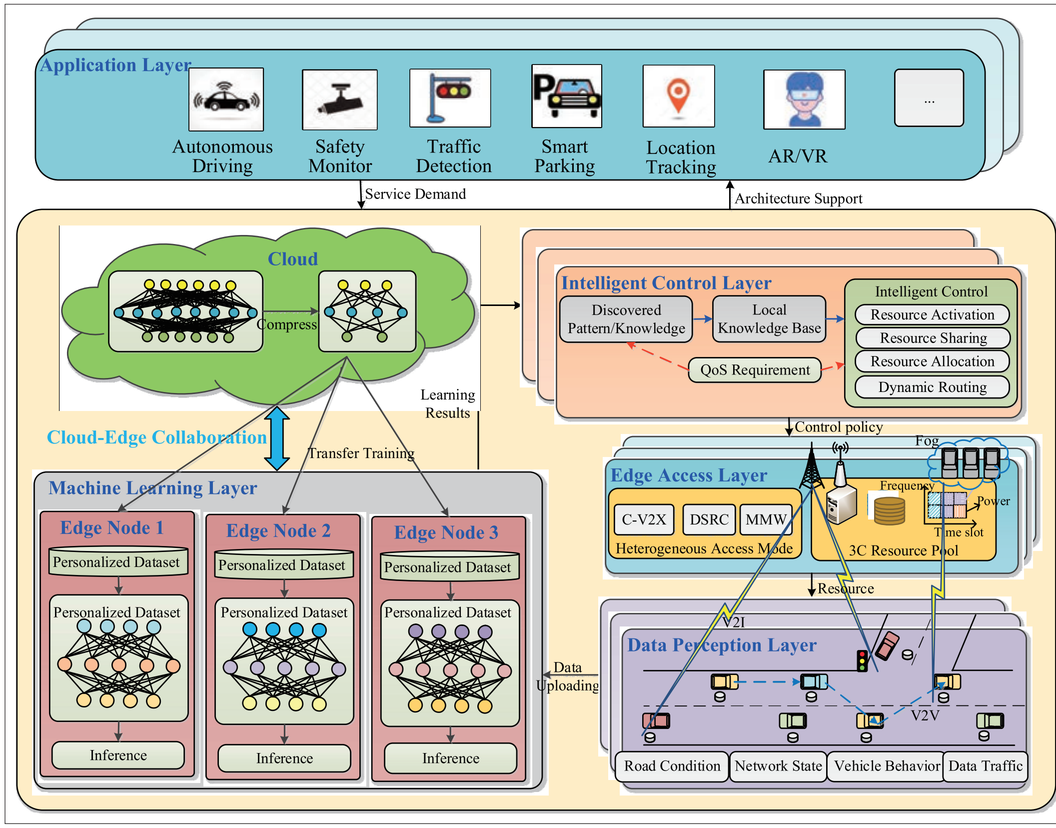

FIGURE 2. Intelligent service-oriented edge resource management architecture

Challenges

Although researchers have done a lot of work in taking parked vehicles as the edge infrastructure for improving network service capabilities in vehicular networks, most of these efforts have focused on the schedule optimization of edge resources, and less involved in the activation and deployment of resources in parked vehicles at the minimum cost. In addition, without the knowledge fully extracted from network data, these non-intelligent network resource management solutions have defects such as high complexity, poor flexibility, and poor scalability. How to extract knowledge from network data to guide edge resource activation is a big challenge.

Intelligent Service-Oriented Management of Extensive Edge Resources

In this section, we design an intelligent service-oriented edge resource management architecture for future vehicular networks in 6G, which supports data perception and machine learning. Characteristics of service requests and edge resources, extracted through data mining, are adopted as references for adaptive coordination between resources and services.

The concept of EI capability, introduced into this architecture, represents the efficiency and performance that an edge node executes AI tasks. Executing a task may include computing, caching, and transmitting process. For an edge node, its EI capability has a positive correlation with the 3C resources it possesses. A certain number of neighboring edge nodes can form a fog, within which nodes complement each other in EI capability by sharing resources. Here the EI capability is defined as a five-element tuple (Accuracy, Latency, Energy, Memory footprint, Spectrum), which is abbreviated as ALEMS. For a specific application, Accuracy is the internal attribute of AI algorithms. To execute AI tasks on the edge, some algorithms have to be converted into lightweight alternatives by compressing the size of models, resulting in a reduction of accuracy. Better EI capability means that the edge node has enough computing resources and is able to execute algorithms with higher accuracy. Latency represents the retraining time of a general model and the inference time of running a trained model on the edge. To measure Latency, the average latency of completing multiple tasks is calculated. When running the same model, Latency represents the efficiency level of the edge. Energy refers to the power consumption of the hardware when executing retraining and inference tasks. Memory footprint is memory usage when running an AI model. Memory footprint indicates the cache requirements for the edge tasks. Spectrum indicates the communication resource requirements for transmitting data. For a specific application, there are determinate minimum ALEMS requirements. To satisfy these requirements, it is necessary to select edge entities that can provide enough residual resources with sufficient EI capability.

As shown in Fig. 2, there are five layers in this architecture, including the data perception layer, edge access layer, machine learning layer, intelligent control layer, and application layer, which will be detailed below.

Data Perception Layer: Perception modules such as sensors, cameras, and RFID receivers, installed at infrastructures and intelligent vehicles, can continuously generate a large amount of road or network environmental data. These data contain information on traffic flows, road conditions, vehicle motion status, network topology, network resource utilization, traffic load, wireless channel gain, and so forth. Nodes in the data perception layer have limited storage space for temporarily caching data, which will be uploaded to nearby edge nodes in batches soon.

Machine Learning Layer: The large amount of data generated in the data perception layer will be uploaded to the machine learning layer for processing and analyzing. Due to the limited EI capability, it is difficult for the edge to train a perfect AI model alone. Hence, we suggest a general model be trained at the cloud first, using the public traffic-related data the cloud stores. In order to reduce the requirements for computing, storage, and other capabilities of the edge, this general model will further be compressed without bringing significant influence on its accuracy. Common compressing methods are parameter sharing, tensor decomposition, and channel pruning. The compressed baseline model only applies to normal traffic conditions; hence it is downloaded from the cloud to the edge for being retrained by transfer learning. Taking local personalized data as inputs, the edge will build personalized models that have better performance and robustness for specific traffic conditions. These edge models can be used for executing inference on the edge. Finally, the real-time learning results including macro-level network states and micro-level vehicle behaviors are sent to a knowledge base. Some urgent commands are delivered to the resource layer to be executed directly. The machine learning layer plays an important role to achieve autonomous intelligent coordination between resources and service demands.

Edge Access Layer: Beyond traditional infrastructures such as base stations and RSUs, parked vehicles also provide edge resources in order to satisfy the wide range of vehicular application requirements. To compensate for resource consumptions, resource pricing is an effective incentive approach to encourage parked vehicles to participate in edge services. Resource transactions are implemented between the edge resource layer and the data perception layer. A virtual resource pool with a uniform abstract representation for multi-dimensional heterogeneous resources is constructed in this layer. Then the dynamic matching between virtualized resources and services is achieved under the control of the upper layer, the intelligent control layer. In addition, based on the decisions provided by the intelligent control layer, the same or different types of edge nodes in an adjacent area can form a collaborative fog. Integration and sharing of heterogeneous resources can be achieved in the fog.

Intelligent Control Layer: The knowledge on macro states (e.g., traffic volumes) or micro behaviors (e.g., maneuver of a vehicle) is discovered through deep learning in the machine learning layer, and then delivered to a local knowledge base. During the learning progress, the edge knowledge base provides the labeled data containing user demand characteristics so that learning results are constantly revised. Once a local knowledge base collects new knowledge items, it will interact with its neighboring edge knowledge bases to enrich their knowledge and be a guide for local knowledge discovery. Under the guidance of the knowledge bases, intelligent control entities make intelligent decisions on resource management, including activating, sharing, integrating, and scheduling edge resources. The decisions are converted into the corresponding control commands and sent to the edge resource layer for implementation.

Application Layer: Typical future vehicular applications mainly include: autonomous driving, safety monitor, traffic detection, smart parking, location tracking, traffic behavior guidance, intelligent entertainment, human-vehicle interaction based on voice assistants, holographic images, extended reality (XR, which is a combination of VR, AR and MR), and so forth.

All the layers in the EI-assisted resource management architecture interact with each other. By analyzing the data that characterize traffic/network conditions, edge knowledge bases are built. The knowledge can be used for the prediction of road traffic patterns, network resource characteristics, and user request volumes, guiding edge resource management. An intelligent self-adaptive provision of resources for vehicular applications can be finally achieved. The information interactions among layers form a closed loop to ensure the validity and consistency of data forwarding rules, so as to make effective control decisions under the necessary constraints.

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A Case Study

In this section, we propose a prediction-based edge resource activation scheme as a case study of intelligent controll under the EI-assisted resource management architecture. It selects the minimum number of parked vehicles as auxiliary edge nodes according to the predicted service request volume, to avoid wasting resources on the precondition of fulfilling user demands.

Conv_LSTM-Based Traffic Prediction

Obviously in the 6G era, each smart vehicle running on the road has resource demands for supporting its necessary applications. Macroscopically, there is a positive correlation between the resource demand and the number of users. Edge resource activation decisions can be made based on the predicted traffic volume in each area. To predict the number of vehicles in a certain area, we process a vehicle trajectory dataset and convert it into a traffic dataset. The traffic data mainly include spatial and time features, which refer to the number of vehicles in a certain area at a certain time slot, respectively. Spatially, the whole area is divided into m*n squares with flexible granularity. Global Positioning System (GPS) coordinates included in the trajectory dataset are converted into the coordinates of the squares. At every sampling time slot, the number of vehicles in each square is counted. Deep learning is advantageous in data mining. As a deep learning model, the convolutional neural network (CNN) [12] has an outstanding performance in spatial feature mining, where residual learning is introduced to simplify the network training when the network becomes deeper. Meanwhile, LSTM is excellent in long-term time series prediction. Therefore, we put forth a network model based on the CNN

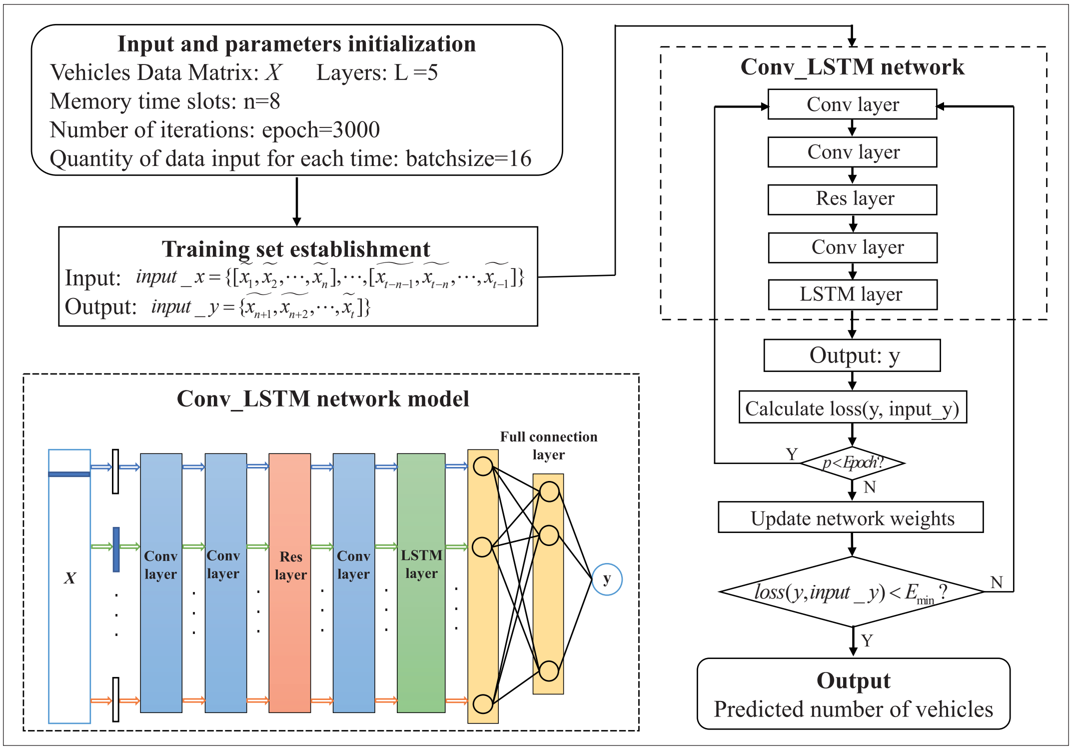

FIGURE 3. Flowchart of Conv-LSTM-based traffic prediction.

and LSTM structure, denoted by Conv_LSTM. The flowchart of the Conv-LSTM-based traffic prediction is shown in Fig. 3.

The Conv_LSTM model is composed of a convolution layer, a residual layer, an LSTM layer, and a full connection layer. Its input is a traffic dataset that is expressed as a time series vector $X = \{x_t, t = 1, 2, ..., T\}$. Each element in the vector represents the number of vehicles in a square at a time slot. Details of each layer are as follows.

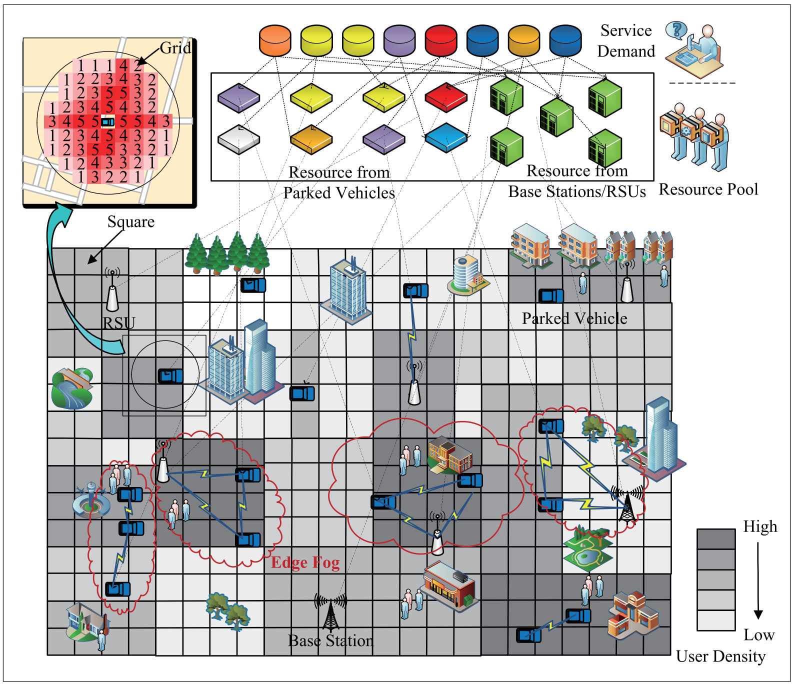

FIGURE 4. Matching between resource pool and service demand with a user density map and vehicles' coverage maps.

In the *convolution layer*, the forward propagation process is as follows. First, two convolution layers are used to extract the spatial features of time series traffic data. The traffic information of each local area is acquired by sliding a 2-D convolution kernel filter. Second, local traffic features are aggregated to form global traffic features. Finally, through adding a bias and applying an activation function, the output of the convolution layer is obtained, that is, the spatial features of the traffic in the adjacent squares.

The spatial features are put into a *residual layer*, which consists of four successively connected residual elements.

The output data from the previous layer are fed into a LSTM layer for extracting time features. The *LSTM layer* is composed of several LSTM blocks and each of them corresponds to a time slot. The time-spatial features of traffic data are fed into a *full connection* layer and the output is the number of vehicles in each area in each time slot.

The whole dataset is divided into a training set, a validation set, and a test set in a certain proportion, for training and testing our Conv_LSTM network. In the training phase, we adopt mean squared error (MSE) as the loss function. To optimize the deep neural network, we use the RMSprop algorithm [13] to adjust the learning rate adaptively. A back-propagation algorithm is also used to update network parameters, in order to minimize the number of network errors. In this way, the model can predict real-time traffic more accurately.

On-Demand Resource Activation

Based on the predicted traffic, a user density map could be built, where the darker color represents the higher density and more resource demands, as shown in Fig. 4. We can see that some adjacent squares with similar user density are merged into a large functional square. Parked vehicles are widely distributed throughout the whole area. To satisfy users' service demands, a collection of parked vehicles that form a resource pool is selected as edge nodes. Since deployers have to pay to the selected parked vehicles for their resource consumption, how to fulfill demands with a minimum number of parked vehicles is a key point. We need to obtain the coverage map of each vehicle first. However, Free-space propagation models are obviously not suitable for the parked vehicles in the urban city due to obstructions such as fixed buildings, trees, moving trucks, and so on. Most existing studies treat vehicular networks as ideal graphs of nodes and straight lines. Such simplifications misrepresent real-world road networks. Thus, we suggest that each parked vehicle broadcasts a measurement signal beacon no less than once per second, and each user reports its received signal strength with its location back to the parked vehicle. Under an area partition with smaller grids, a coverage map showing its received signal strength can be formed, as shown in the top left corner of Fig. 4. Note that the boundaries of the coverage map lower than a pre-set signal strength threshold are clipped.

Although we define the EI capability as ALEMS (including Accuracy, Latency, Energy, Memory footprint, Spectrum), we only consider applications that have Spectrum requirements in this specific case study. The other four elements will be further considered in our future work. Imagine all the parked vehicles have the same EI capability (i.e., available spectrum bandwidth). Those functional squares with high user density need to be overlapped by multiple parked vehicles. We define the service saturation of the ith square is $\varsigma_{sat}(i) = n_R(i) \cdot R_{serv}/R_{req}(i)$, where $n_R(i)$ is the number of parked vehicles covering the square. R_{serv} and $R_{req}(i)$ are the service capacity of a parked vehicle and the user demand in the i^{th} square, respectively. Service saturation is a measure of redundancy of active parked vehicles. $\varsigma_{sat}(i) > 1$, which means the i^{th} square is covered by more than a single parked vehicle, is desirable from a standpoint of availability. That is helpful to cope with the case when a parked vehicle with the RSU role is removed from the network. However, excessively high saturation for a square means that the activated parked vehicles are stacked too close, resulting in a waste of resources. In practice, an efficient algorithm will keep a mean saturation of 1.44 [9].

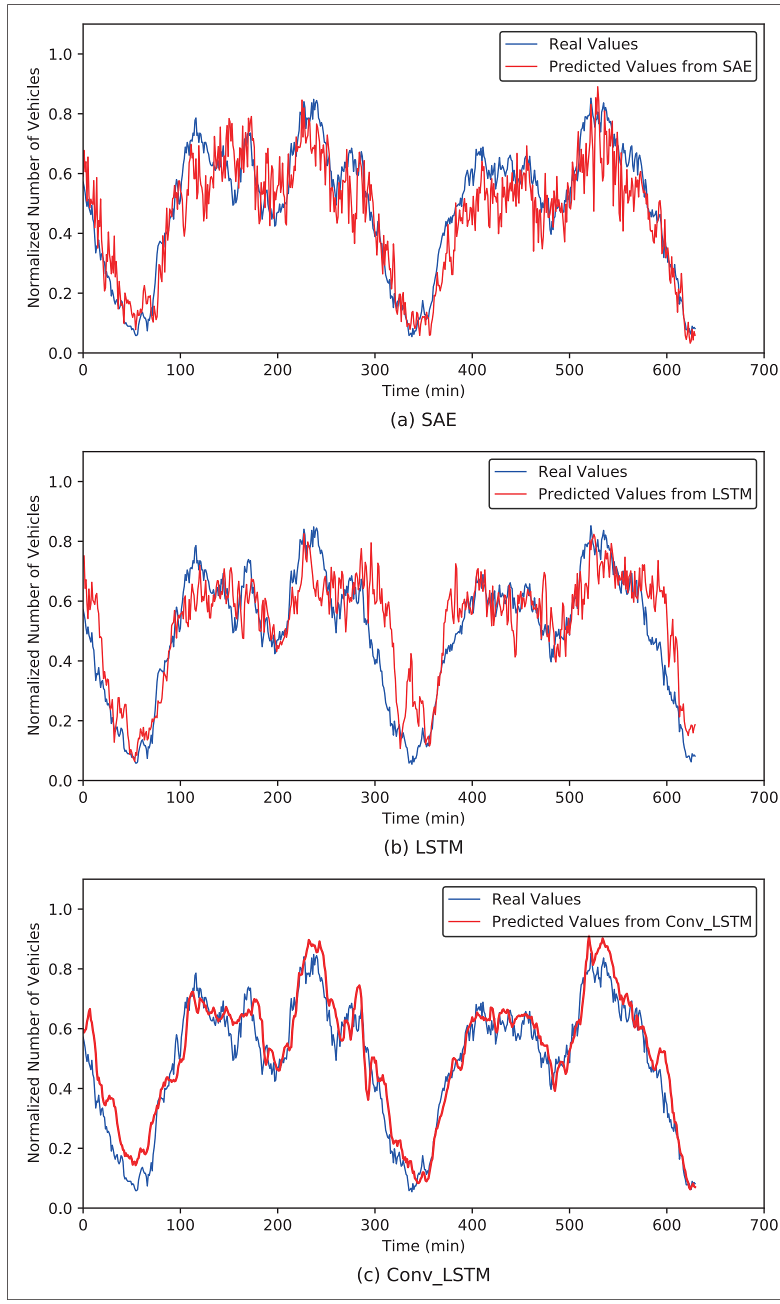

FIGURE 5. Comparisons of real values and predicted values from three models: a) SAE; b) LSTM; c) Conv_LSTM.

Simulation Results

We implement the proposed Conv_LSTM model in Tensorflow. Then we further implement our prediction-based resource activation method. The performance is evaluated from two aspects: the prediction accuracy of the Conv_LSTM model and the deployment cost in the resource activation scheme.

Prediction Accuracy

We train the Conv_LSTM for 3000 epochs, using a 3*3 convolution kernel. The values of the learning rate, the decay rate, and the dropout rate are set as 0.1, 0.9, and 0.4, respectively. The batch size is 16. The CabSpotting dataset [14], containing mobility traces of about 500 taxis driving around San Francisco for 30 days, is taken as the vehicle trajectory dataset. After pre-processing, the vehicle trajectory dataset is converted into a traffic dataset containing 3500 pieces of data. The 60 percent of the available data are allocated for training. The remaining 40 percent of the data are equally partitioned and taken as validation and test data sets.

We compare our Conv_LSTM model with the two existing prediction models: LSTM and stacked autoencoder (SAE). The comparisons of real values and the predicted values generated by the three models are shown in Fig. 5. We can see that the predicted values from the Conv_LSTM model are much closer to the real ones than those from LSTM and SAE. After 300 epochs, the mean squared error (MSE) of the Conv_LSTM model is 0.00481, while the MSE values of LSTM and SAE

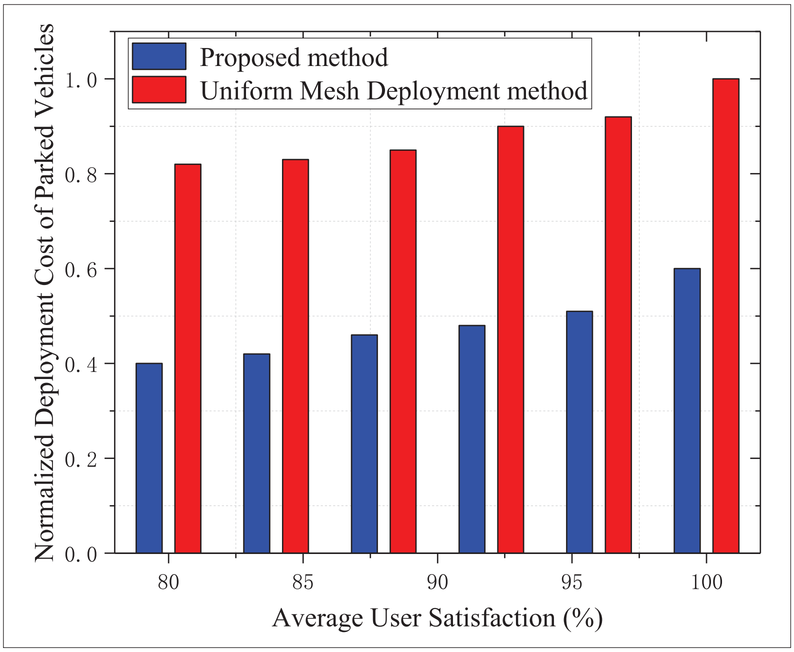

FIGURE 6. Normalized deployment cost of parked vehicles with different average user satisfaction.

are 0.00508 and 0.00510, respectively. The reason is that Conv_LSTM can extract time and spatial features of traffic data and avoid overfitting with the help of the residual layer.

Deployment Cost

We assume that there is no base station or RSU in an area for simplification, and some parked vehicles can act as edge nodes. Deployers have to pay for consuming the resources of each activated parked vehicle. Excessively activating the parked vehicles will increase deployment costs; in the contrast, insufficiently activating will decrease the satisfaction of users' resource needs. For a user, we define its satisfaction as the ratio of the allocated resources to the requested resources, whose value is not over 1. The average user satisfaction is an average value of user satisfaction. The normalized deployment costs with 80–100 percent user satisfaction using different resource activation methods are shown in Fig. 6. The Uniform Mesh Deployment [15] method is taken as a comparison scheme, which distributes RSUs uniformly on the map, regardless of the expected average traffic density. We can see that our proposed prediction-based method decreases the deployment cost significantly. The reason is that under the intelligent resource management architecture, the knowledge extracted from network data can guide the deployment of edge resources. The corresponding amount of resources from parked vehicles are activated according to the predicted traffic density. It shows that the traffic density prediction is useful to help activate edge resources as needed.

Conclusion and Future Work

In this work, we have introduced extensive EI in future vehicular networks, where parked vehicles are taken as auxiliary edge nodes to provide extensive resources. An intelligent service-oriented edge resource management architecture has been proposed to achieve intelligent coordination between extensive edge resources and services. As a case study of intelligent resource management under the proposed architecture, a Conv_LSTM-based resource activation method has been designed, which activates parked vehicles according to the predicted traffic volume. We also have demonstrated that the Conv_LSTM model achieves high prediction accuracy, and the proposed resource activation method can guarantee user satisfaction with lower deployment cost.

In addition to parked vehicles, unmanned aerial vehicles (UAVs) hovering above ground have a wide range of coverage, showing the potential to act as auxiliary edge nodes. It will be our future work to explore more extensive edge resources for EI through the inclusion of UAVs.

Acknowledgments

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Biography

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