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Fast Connectivity Construction via Deep Channel Learning Cognition in Beyond 5G D2D Networks

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Abstract: Along with the recent advance in wireless networking and data processing technologies, demands for low latency communication (LLC) are increasing in a wide variety of future-driven autonomous applications such as a smart factory, self-driving cars, and so on. The fifth generation of cellular mobile communications (5G) will cover this need as one of three key capacities in their usage scenarios: enhanced mobile broadband (eMBB), massive machine type communication (mMTC), and ultra-reliable low-latency communications (URLLC). The 5G systems are composed of mobile devices and various internet of things (IoT) devices for sensing, acting, and information services; they configure diverse networking topologies such as direct mobile-to-mobile, also known as device-to-device (D2D). In the 5G D2D network systems, the network topologies are easily broken because of the mobile devices such as smartphones, IoT devices, and so on. Thus, for the highly flexible and extensible 5G D2D network systems, mobility support for the mobile devices is necessary. In this paper, we first explore the mobility issues in beyond 5G D2D. Since there are static and mobile elements in the 5G application domains such as the smart factory, overall mobility would lead to highly frequent topology reconfiguration or connectivity reconstruction. Thus, latency-related problems derived from topology changes and connectivity failures due to the mobility are addressed. To handle the problems, a fast connectivity construction scheme, denoted by LMK, is proposed with a deep neural network dealing with learning on radio signal information in order to achieve the LLC. Evaluation results demonstrate that the proposed framework can provide reliable connectivity for the MAC layer link with a low latency data transmission.

Keywords: low latency communication; out-band device-to-device; 5G

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1. Introduction

The integration between computing and networking environments has been widely promoted for intelligent service provisioning to end users and effective resource usage for the next generation of manufacturing. This convergence paves the way toward the information and communication technologies (ICT) revolution, denoted by IoT. IoT is the network of physical devices, vehicles, home appliances, and other items embedded with electronics, sensors, actuators, and connectivity which enables these things to connect, collect and exchange data [1]. The IoT paradigm is changing the way people interact with things around them and our everyday life for activities, tasks and rituals in an easy using information and intelligence hidden in the network linking the things [2]. This pervasive paradigm of IoT increases the value of information generated by many interconnections between people-things and things-things and the transformation of the processed information into knowledge for the benefit of mankind and industries.

IoT is leading to the substantial deployment of ubiquitous computing with many applications built around various types of sensors and actuators. During the past decade, most issues at device levels have been solved and nowadays, there is a growing trend in the integration of sensors and novel communication technologies such as D2D for information-based smart systems [3]. IoT is taking the center stage as the devices are expected to form a significant portion of the 5G network that is on the horizon. IoT communication through D2D will complement intelligent data analysis expected to drastically change the landscape of various industries and our daily lives [4]. In other words, the proliferation of connected smart devices with receiving the boost in data analysis via artificial intelligence (AI) technologies leads to further innovation of manufacturing into the fourth industrial revolution and intelligent living areas such as smart homes and communities.

This paper brings up a key point of technical issues to realize the integration vision of IoT and the 5G: Context-awareness [5]. To provide adequate intelligent services, systems should be aware of information on surrounding service components and their present status, and automatically adapt to dynamic situations. Data sensing and acquisition are the first main functionality and cognitive computing provides information and intelligence for smart applications. During/after service provisioning, service components also deliver feedbacks as improving context. Each element and process are adopted on different devices as a separated service component or embedded into one device according to the application depth from global adaptation to very local controls in a service domain.

The context-aware service loop can be applied to D2D based social networking [6], smart home with connectable intelligent appliances [7], next generation manufacturing via machine-type D2D networking [8], self-driving cars with cameras and huge numbers of sensors, and so on. Those applications are composed of highly heterogeneous devices, especially for mobility and computation capacity [9]. It means that the context-aware smart application system should rely on dynamically-reforming D2D networks that easily harm the fundamental requirements of smart applications such as real-time collaboration and sustainability.

In the 5G network systems, as a key component of Industry 4.0, robotics and autonomous systems require eMBB, mMTC, and URLLC. The first 5G standards, called Release 15 New Radio (NR), only support some level of flexibility and scalability of configurations as a general framework [10]. Although the 5G NR supports some requirements, URLLC cannot be guaranteed under the 5G NR defined by the 3rd Generation Partnership Project (3GPP) [11]. Thus, it should be applicable for limited use cases and optimized.

This paper addresses the seamless network coverage issues to support URLLC in beyond 5G D2D, and then proposes a solution based on the context-aware service loop to handle the issues. The contribution of this study will be represented as follows:

- This paper makes closely investigates of seamless connectivity issues with mobility which are eventually related to real-time demands on applications based on beyond 5G D2D networks.
- In addition, the fast connectivity construction framework relying on on-node analyses of networking contexts is proposed with the goal achievement on low latency.
- On-node analyses are designed through a light-weight deep neural network (DNN) technique, and it is examined by various experimental scenarios.

The rest of this paper is organized as follows. In Section 2, we present the state-of-the-art in terms of the 5G networks, D2D, and cognitive computing. In Section 3, we explain of our fast connectivity construction scheme. Then, we address DNN based analyses in detail in Section 4. Finally, we conclude this paper with further discussions and future works in Section 5.

2. D2D, IOT, and Context-Awareness

2.1. D2D Communications in Smart Applications

5G D2D is recently receiving more interest as a critical technology promoting the industrial 4.0 paradigm and many daily life applications with situation-adapted intelligence since D2D is able to support machine-type communication, flexible/extensible connectivity to the Internet, and temporal dynamic inter-connectivity. Figure 1 presents those scenarios with D2D and other 5G connectivity techniques. Particularly, Figure 1a illustrates the smart factory scenario with various IoT devices such as drones, autonomous mobile robots, and producing robots which can be connected via a range of the 5G connectivity techniques such as small cells, D2D, and Drone-supported communication [9]. Then, D2D takes the role to inter-connect among diverse cells as well. In the other case, social networking is configured through the D2D technique, as shown in Figure 1b, where two social groups are formed via D2D. It means that the members of each group might be willing to open their own smart mobile device capacity to other members since D2D relies on sharing resources of devices in communication, which is the biggest reason to prevent this novel paradigm deployment nowadays [5,6].

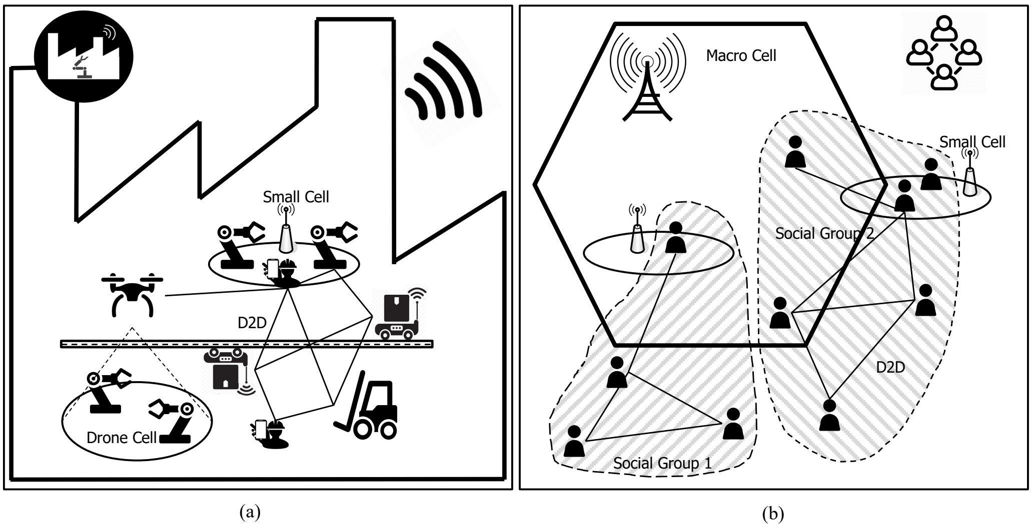

Figure 1. 5G D2D Based Smart Applications with Mobility and LLC Issues: (**a**) The Smart Factory Scenario and (**b**) The Social Networking Scenario.

Such D2D communication is fulfilled by not only radio access technologies, e.g., cellular series, WiFi, and Bluetooth, but also various routing techniques with many different network topologies according to diverse environmental and situational properties [12]. D2D communication can configure tree or mesh networks via inband or outband spectrums and be configured in conventional control and data planes or direct ways without support from an eNB in 4/5G. Moreover, it can support offloading from a macro cell to small cells, as well as isolated networking in out-of-network coverage [13]. Such D2D networks are minutely composed of three networking phases: Infrastructure-to-Device (I2D), Device-to-Infrastructure (D2I), and Device-to-Device (D2D) networking. Each networking phase can be performed in single-hop or multi-hop communication.

D2D supports highly flexible and extensible networking technology based on the moving devices such as smartphones and smart IoT devices as represented in Figure 1. It means that the network topology is easily broken due to the mobility of various devices, which can affect communication performance such as latency and reliability. Thus, connectivity guarantee and fast network topology recovery should be taken into consideration for the smart applications that rely on D2D architecture for real-time and reliable communication. Fast connectivity is essential for D2D network sustainability because of the battery constraints of D2D to ensure network lifetime [14]. Furthermore, the mobility of devices may bring about the discontinuation of established connection sessions in D2D system [15]. As a result, there are several challenges associated with D2D communication.

2.2. *Context-Aware 5G Systems with Mobile Edge Computing and D2D*

The development of 5G D2D systems for intelligent applications is continuously expanding toward smart homes, industrial plants, and intelligent transportation systems [16]. The 5G systems are expected to play a critical role in supporting the IoT with their connectivity and ubiquitous coverage [7]. The IoT needs computation and storage ability to support the sensors and actuators. The smart service based on cognitive computing with the IoT will be fulfilled for time-constrained applications. Recently, mobile edge computing has been increasingly used in various application designs. In the 5G mobile systems, mobile edge computing has been recognized as a key enabling technology for a wide range of applications and scenarios [8]. D2D networks are a novel paradigm for mobile edge computing in the 5G and beyond 5G networks because of energy efficiency, reduced delay, limited interference, and so on [17]. A lot of mobile devices execute sustainable computation tasks without connecting the base station or the core network in D2D networks [18]. Furthermore, D2D networks support the applications for the sensing data to the mobile edge. However, there might be many hurdles for reliable and fast data delivery over D2D networks since D2D is composed of mobile devices, and they configure multi-hop mesh networks where connection links between devices can be frequently changed [13].

Cognitive computing for context-awareness has been developing for the last couple of years to generate information or intelligence eventually. The state-of-the-art studies have been based on DNN, which is denoted by deep learning. The DNN technologies such as multi-layered neural network, convolutional neural network (CNN), and recurrent neural network (RNN) are exploited in various environments for smart applications [19]. These studies have been worked on communication or IoT related services such as cognitive radio networks [20], indoor localization [21,22], wireless signal identification [23], mobile data sensing [24], and so on. These studies are also following the sequence of service loop mentioned above, and all the cognitive computing in them are based on one model: train offline-use online. Data acquisition is fulfilled as pre-operation separately; then, data training with DNN model is performed at the mobile edge as an offline operation. The trained weight of the DNN is used for the real-time sensory data. However, these methods for the DNN are not suitable for D2D based time-critical application cases because D2D network connectivity highly suffers from the mobility of component devices and this situation frequently happens before making connection to the mobile edge. Thus, on-node cognitive computing should be considered.

3. Fast Connectivity Construction Framework

Time-constrained communication for managing assets and goods in the on-site production and logistics sectors is one of the essential demands on reliable management to avoid faults and improve the overall manufacturing automation efficiency for the smart factory. Each device for mobile social group communication needs to continuously connect with each other and the Internet. Thus, D2D network connectivity should be constructed all the time to tightly and intelligently deal with low latency against mobility. This section proposes a fast connectivity construction framework based on the DNN-based cognitive computing.

As mentioned in the analyses of related work, it is not possible to fulfill the offline training for predicting information of D2D networking connectivity since D2D networks are frequently detached from the mobile edge computers where the offline training is performed. This is because that D2D networks can be configured out of the mobile network coverage even via outband signaling. Therefore, the proposed fast connectivity construction framework is designed with on-node DNN-based learning. It means that a smartphone should be able to perform context acquisition, DNN computation, and intelligent actions to satisfy the low latency requirement against mobility. The proposed DNN is a light-weight neural network, not taking high computation power and trained by a not large amount of data batch.

3.1. Framework Operations

In this subsection, operations of our fast connectivity construction framework are presented. As shown in Figure 2, there are two phases for this framework that mostly covers the context-aware service loop. In the training phase, a mobile device in a D2D network acquires context and trains the context on the light-weight multi-layer neural network (LMK). In the connecting phase, the mobile device asks for connectivity path prediction of LMK to calculate the adequate networking path in the current time and location. Furthermore, both phases in the proposed framework are carried out within each mobile device in a D2D network.

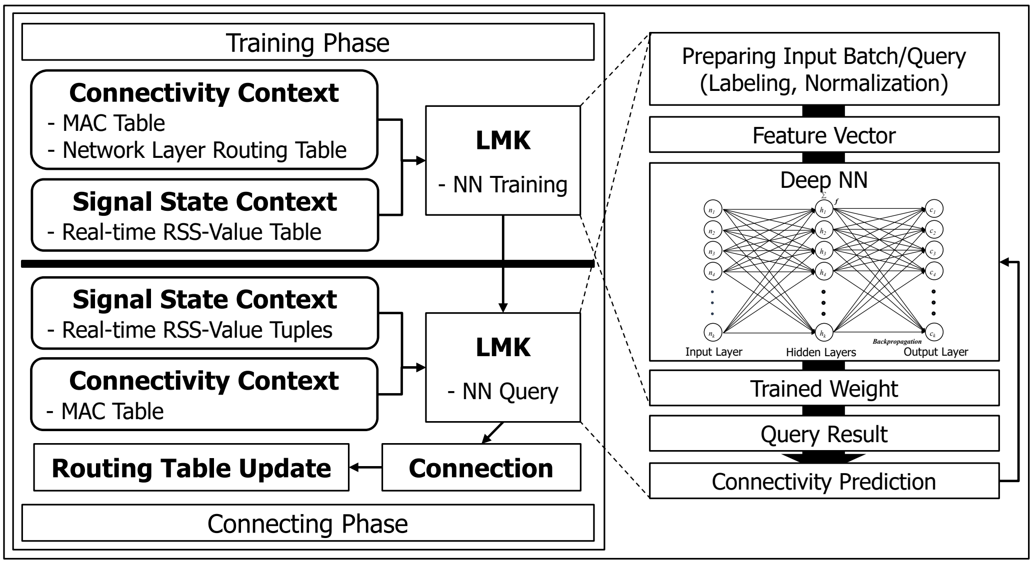

Figure 2. Fast Connectivity Construction Framework with On-node Training and Query.

There are two types of context in the training phase as DNN training data sets: connectivity context and signal state context. The connectivity context is about MAC layer link information and network layer routing path data over the MAC layer links. The signal state context is currently measured by radio signal strength (RSS) values, and they are prepared as a table. All the data are exploited to train LMK. In other words, when a mobile device joins a D2D network such as a producing sector in the smart factory or a social group over social networking domains, it starts acquiring such context during a round and training the context into LMK. After that minimum condition for using LMK, the device continuously maintains the LMK in update-to-date status.

In the connecting phase, each mobile device in a D2D network prepares two contexts in terms of signal state context for real-time RSS values and connectivity context in the MAC layer. The mobile device queries connecting path prediction for updating the routing table in the network layer to the pre-trained LMK. Then, the mobile device performs the control plane for networking and updates the routing table in the network layer. Finally, each mobile device can be ready to send data packets to other mobile devices in the D2D network.

3.2. Light-Weight Multi-Layer Neural Network

The designed light-weight multi-layer neural network, denoted by LMK, is based on k numbers of nodes in the input layer, hidden layers, and output layer. The number k indicates the maximum number of the MAC layer links and the hidden layers use minimum numbers of k nodes in LMK. LMK uses the Sigmoid function as the activity function, and then error backpropagation is calculated at the output and distributed back through the network layers. In order to reduce computing overhead, LMK does not exploit the convolutional layer and the SoftMax function. When the input data is prepared, the connectivity context and signal state context are utilized to make the label for training data, and the prepared input batch is normalized. LMK carries out the training of data. During the training, the error against the label is propagated backward. After multiple numbers of epochs, LMK can be ready to receive queries with the trained weight of its own neural network. Then, a query can be conducted in LMK by preparing a data set with real-time

RSS values and current MAC layer links. LMK provides query in the trained NN and decides on connecting paths as the prediction result.

LMK is composed of multi-layer perceptron (MLP) based on DNN [25]. The MLP is a type of neural network using the backpropagation method and should be pre-trained by a lot of data to calculate the required prediction accuracy [26]. Equation (1) represents the inputs, weights, and bias that are computed for MLP.

$$f_j = \sum_{i=1}^{n} w_{ij} \cdot x_i + \beta_j, \tag{1}$$

where n, x_i, β_j, and w_{ij} show the number of inputs, the input variable of i, bias term, and the connection weight respectively. The Sigmoid function is used as the activation function in the MLP model. The Sigmoid function is described in Equation (2), and the output of the neuron j can be measured in Equation (3) as follows [19,25]:

$$s_j(x) = \frac{1}{1 + \exp(-f_j)}, \tag{2}$$

$$y_i = f_j \cdot \left(\sum_{i=1}^{n} w_{ij} \cdot x_i + \beta_j \right). \tag{3}$$

4. Performance Analysis

In this section, the performance of the proposed framework with on-node cognitive computing is evaluated. For the performance analysis, the proof-of-concept based on a smart mobile device is developed [27,28]. All the process of the proposed framework, including LMK, is implemented on the smart mobile device. The detailed implementation and experimental environments are elaborated in the following subsections.

4.1. Proof-of-Concept and Testbed Setup

The proof-of-concept is developed based on four devices (one smartphone and three laptops) that configure an out-band D2D network via WiFi [14]. In the D2D network system, one smartphone has its mobility with maintaining network connection to the fixed laptops through the fast connectivity construction for low latency communication. Our D2D network system and LMK are implemented with the Java programming language. A summary of the parameters used in the simulations is shown in Table 1.

Table 1. Simulation parameters.

Parameter	Value
D2D Type	Outband D2D with WiFi [14]
Number of Nodes	4 (3 fixed and 1 mobile) [29]
Number of Packets	70∼100 [30]
Moving Speed	About 5 km/h [29]
DNN Epoch	100∼1000
Number of DNN Layers	3∼9

Three laptops in the network system are the node denoted by DN1, DN2, and DN3, respectively. DNs are performed as access points with their own MAC link names. The smartphone has mobility with 5 km/h moving speed in the coverage of the DNs and acquires context while moving [29]. If the smartphone moves out of coverage of the DN, it tries to make a connection to another DN because the smartphone might be able to lose L3 connection to the DN. When the smartphone moves forward passing through the DNs, latency time is measured to maintain connection to the DN, which shows the best link quality. Thus, the smartphone is always ready to send data packets to the DNs without delay for making a connection [30]. In addition, the performance related to LMK with changes in DNN properties is investigated in order to check through the appropriate setup for cognitive networking applications based on on-node deep learning.

4.2. Experimental Results

Figure 3 shows comparison results on the prediction success ratio of LMK according to the number of epochs for context training as well as the number of DNN layers of LMK. As shown in Figure 3a, the prediction success ratio converges to 0.86 at 900 epochs within 6.48 s of the training time. Figure 3b represents the results and changes in the number of DNN layers from 3 to 9. The results show that the number of layers affects decreasing prediction success ratio. Thus, 3 layers of DNN training are the best performance of prediction success ratio and training time.

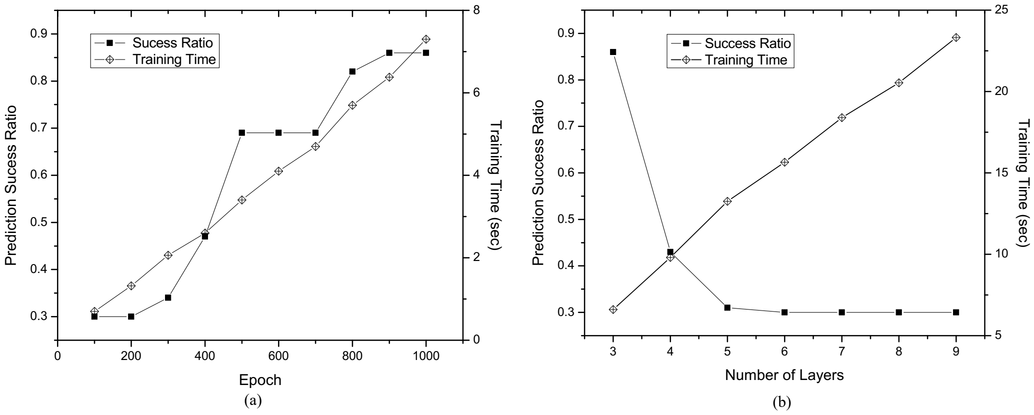

Figure 3. Comparison of Prediction Success Ratio: (**a**) Numbers of Epochs and (**b**) Numbers of DNN Layers.

Figure 4 shows the comparison results for latency. The latency time of DN1, DN2, and DN3 for the proposed scheme is 15, 15, and 19, respectively. For the general connectivity scheme, the latency time of DN1, DN2, and DN3 are 23, 27, and 33, respectively. According to the results, the smartphone can maintain the network connection over the best MAC link to the DNs with low latency even though it is continuously moving. On average, the latency of the proposed scheme in terms of connectivity reconstruction is 11.3 s faster than general connectivity construction.

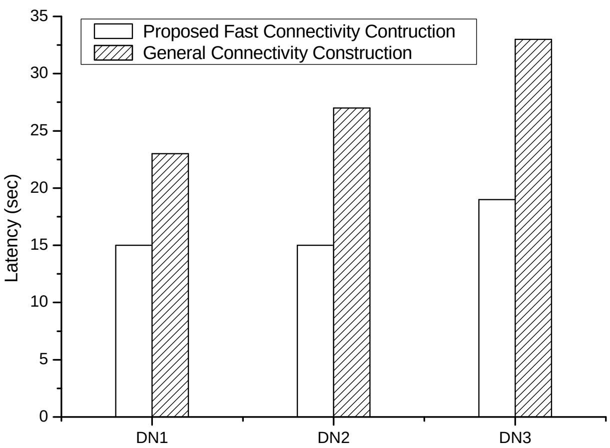

Figure 4. Latency of Routing Paths.

In Figure 5, 100 data packets are transmitted for analyzing the connectivity construction. As shown in Figure 5a, total delivery time of the general connectivity construction take a long time than the proposed scheme because the general connectivity construction maintains the link connection even though the state of the link is not good. In addition, there is a delay in which information to be sent cannot be transmitted for a reconnection time. On the other hand, since the proposed scheme is based on the MLP that can be used to detect the relative position when a specific signal combination is measured, the best link is selected. Therefore, in the case of D2D communication in which mobile nodes frequently reconnect, the proposed scheme can transmit data with low latency faster than the general connectivity scheme. In Figure 5b, the general connectivity scheme shows that the transmission ratio for packet data transmission is lower than that of the proposed scheme. The proposed scheme shows 100% of packet delivery ratio, while the general connectivity scheme shows 88% of packet delivery ratio.

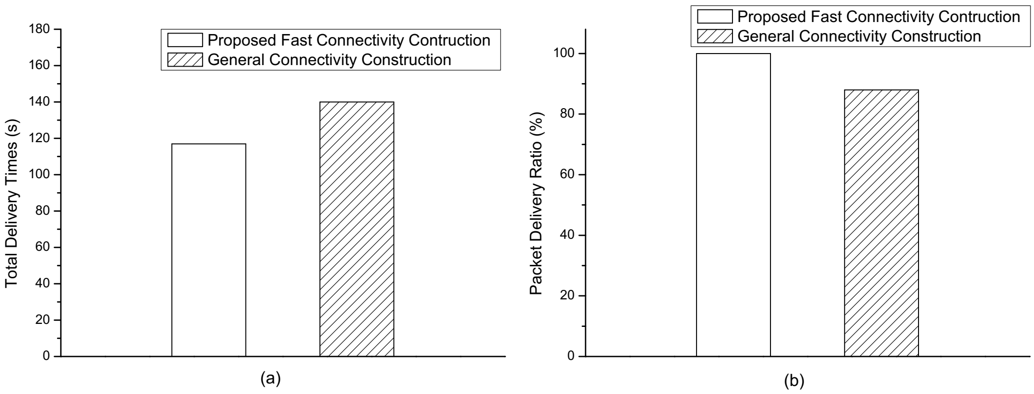

Figure 5. (**a**) Total Delivery times. (**b**) Packet Delivery Ratio.

Figure 6a shows 70 data packets are transmitted while the mobile smartphone moves among DN1, DN2, DN3. The proposed scheme performs direct connection between devices to be transmitted irrespective of the link signal strength, and L3 transmission between nodes can be performed directly. Thus, it can be seen that 70 data packets are delivered directly to each DN. On the other hand, in the general connectivity construction method, data is transmitted only through the connection link to DN1, so both data to be sent to DN2 and DN3 are sent to DN1. Figure 6b measures the total delivery times to transmit the entire data with 70 data packets. The proposed scheme takes 96 s, whereas the general connectivity scheme takes 124 s of transmission time. This means that the proposed scheme shows performance improvement in relation to the transmission delay.

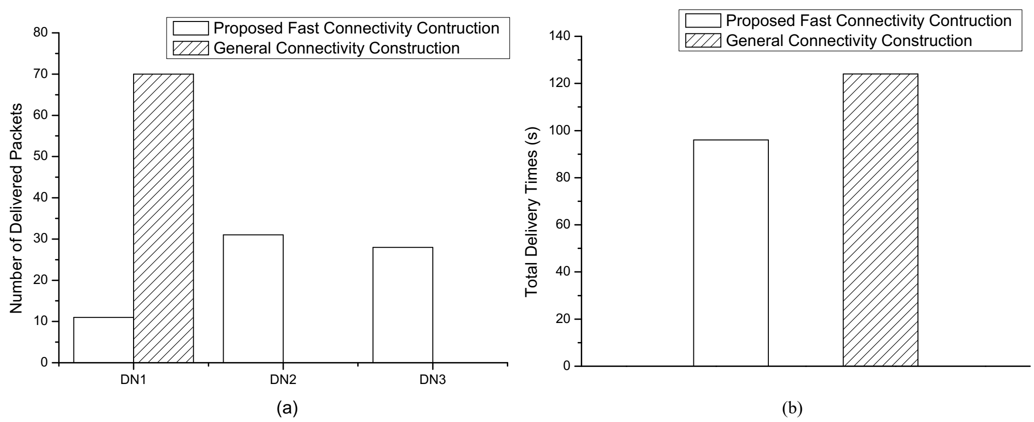

Figure 6. (**a**) Number of Delivered Packets. (**b**) Total Delivery Times.

5. Conclusions and Future Work

This paper investigates network connectivity issues against the mobility of nodes in beyond 5G D2D network, which is receiving increasing interest for supporting future-driven smart applications such as smart factory, the 5G based social group networking, and so on. The fast connectivity construction framework is proposed for time-sensitive smart applications to achieve LLC properties. The proposed framework is composed of two phases: the training phase and connecting phase. In the training phase, data about D2D network context are acquired and trained based on on-node deep learning, named LMK. To calculate the networking path, the mobile device uses the LMK in the connecting phase. Based on the performance analysis, the proposed D2D network scheme can maintain its networking connectivity over the best MAC layer link at 11.3 s faster than general connectivity construction. In addition, we demonstrate that the proposed scheme can transmit data faster than the general connectivity scheme while maintaining 100% of the packet delivery ratio. To improve performance metrics on latency suffering from the handover in D2D networks, the hierarchical deep learning architecture based on mobile edge computing and cloud computing are taken into account as future work. Furthermore, the battery power consumption of mobile devices has increased with a lot of data in the 5G network system. In future works, we will consider the battery power consumption of mobile devices.

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