Resources Allocation for D2D Aided Networks in 6G Industrial IoT

Abstract

The sixth-generation (6G) wireless technology will be the high-level aim for its vision of the next decade and beyond to resolve scenarios expected to raise the ultra-nervous data rate requirements, extreme mobility, and Continuous connectivity. In the 6G era, a vast number of Industrial Internet of Things (IIoT) devices are expected to connect to networks, and the rapid progress in artificial intelligence may enable the realization of smart manufacturing. However, the sheer quantity of IoT devices, enormous data volumes, device heterogeneity, and growing privacy concerns pose challenges to efficient management and service quality in IIoT. This article proposes a device-to-device (D2D) communication-enhanced digital twin-edge network to tackle these issues. This approach incorporates edge computing to bring computational and storage resources closer to end devices, utilizes digital twin technology to bridge the gap between physical and virtual realms, and employs D2D communication to assist resource-constrained IoT devices in achieving everyday communication. Also, to ensure privacy awareness and deploy federated decentralized resource allocation strategy training on D2D communication links, the proposal leverages digital twins with federated reinforcement learning, further amplifying overall network performance. Simulations drastically improve the network performance w.r.t the baseline algorithms with the proposed approach.
Keywords: digital twin, edge computing, federated learning, resource allocation, D2D
communication, and IIoT.

Introduction

The need for faster data transfer, ultra-low latency, and seamless connectivity has grown as a result of the quick development of new technologies like the Internet of Things (IoT), smart cities, vehicle-to-everything (V2X), and extended reality (XR). It is anticipated that the quantity of data traffic and the number of mobile user devices (UDs) will increase at a never-before-seen rate during the next ten years. 5G networks might not be able to meet the changing needs of contemporary applications in light of these growing demands. This is why scientists anticipate 6G even as 5G continues to roll out globally.

Terahertz (THz) communication is one of the main technologies that could enable 6G. Compared to the millimeter waves utilized in 5G, it enables substantially faster data transfer speeds and a wider bandwidth by operating in the 0.1–10 THz range. Because of this, THz technology has great promise for managing the enormous volumes of data that upcoming networks will produce. The Industrial Internet of Things (IIoT) is expected to have more connected devices in the 6G era. Thanks to advancements in electronics and materials, the Internet of Things devices will feature wireless sensors and intelligent processors that generate vast volumes of operational data in real time. Despite the devices having low processing & storage capabilities, an important challenge is how to manage and process data efficiently. Traditional cloud Computing, with respect to its high processing power and large storage capacity, is suited for processing huge volumes of data quickly. However, cloud-based solutions may experience excessive latency and decreased reliability when networks are overloaded with millions of devices. Edge computing can help with this. In IIoT networks, edge computing,g can assist speed up reaction times and increase the effectiveness of data processing by utilizing edge servers' storage and processing capacity. The potential of edge computing to improve IIoT performance—specifically in job offloading—has been the subject of numerous research. In order to manage delay-sensitive jobs in multiuser mobile edge computing environments, for example, one study suggested an autonomous partial offloading system, which would guarantee fewer delays and higher service quality. To lower system expenses, such as task delays and migration costs, a learning-based device-to-device (D2D) task offloading technique was presented in another study. In order to maximize processing power and reduce long-term job delays in edge computing systems, researchers have also looked into resource management techniques based on deep reinforcement learning (DRL). The future of high-speed, low-latency networks is anticipated to be significantly shaped by 6G and edge computing technologies as research into these areas progresses. In particular research, as [10], edge computing has been used to optimize data encoding, which in turn lowers network traffic and latency for cloud-based machine learning (ML) Operations.

A relatively recent technique called edge computing moves data processing, model training, and content distribution closer to the operating and data-generating user devices (UDs). Edge computing reduces the amount of data that must be sent over the core network and helps maintain reliable connections by processing data at the network's edge rather than exclusively using cloud servers. In this system, edge servers are essential because they offer the processing and storage capacity required to improve data processing speed and lower latency in comparison to conventional cloud-based techniques. There are many benefits of integrating edge computing in communication networks, but at the same time, designing 6G edge networks also comes with some challenges. Individually, each of these bands can only serve some of the requirements, e.g., the THz band, due to a high path loss that leads to a short transmission range, is more appropriate for short distances. In an edge network, devices with limited communication capability or not in the coverage area will struggle to connect.
A possible solution to these problems is Device-to-Device (D2D) communication which provides a direct device-to-device link (unmediated by base station (BS)) [10]. D2D communication reuses the available spectrum, thereby optimizing the spectrum usage but can interfere with the cellular links also [11]. Effective resource allocation strategies have been studied for D2D-assisted networks [12], [13], [14], [15]. Specifically in working service migration expenses as users traverse the network. Machine learning (ML) is a key component of DT modeling and optimization strategies. A relatively new approach known as Federated Learning (FL) provides a distributed method of training ML models. Instead of sending data to a central server, FL allows distributed user devices (UD) to train in collaboration with a global model while keeping its local training data, preserving the confidentiality of users [22]. To enhance the security and privacy of DT-based edge networks, [23] introduces a blockchain-driven asynchronous FL scheme. In another study [24], researchers use private, locally stored[12], the authors proposed an energy-efficient resource allocation algorithm based on deep learning (DL) to achieve maximum global energy efficiency while meeting the data rate constraints of cellular users and D2D pairs. In the same way, the approach proposed in [13] description is based on deep reinforcement learning (DRL) to assist in optimizing communication modes and resource allocation in heterogeneous cellular networks. Another research [14] proposed an energy-efficient resource allocation based on carrier aggregation technology. To minimize the overall power consumption of mobile devices while maintaining the quality of service (QoS) for both cellular and high-rate D2D connections.
Researchers presented the "pure D2D model", one of the more versatile resource-sharing frameworks enabling many D2D pairs to reuse resource blocks without affecting the cellular users [15]. Explosive development in artificial intelligence (AI) —particularly the ongoing advancements of machine learning— has prompted a significant shift in industries. In the last decade, a new concept called Industry 4.0 has been introduced, which promotes the incorporation of AI and other advanced technologies to digitize the manufacturing process, improve productivity, and realize smart manufacturing [16]. An effective digitization strategy will be critical for this. The idea of a digital twin (DT), which bridges the gap between the real and virtual worlds, is one of the innovative technologies enabling these advancements. The main function of a digital twin is to create a virtual version of a physical object or process through the use of data processing methods, mathematical modeling, and automatic learning algorithms. Because of its potential to revolutionize manufacturing and industrial processes, Jumeau Digital Technology has lately attracted the attention of academia and industry alike. One of the key benefits of Twin Digital Technology (DT) lies in its capability to facilitate bidirectional data exchange between real-world objects and their digital and analogs. This allows for modeling, checking, predicting, optimizing, and monitoring the corresponding physical systems [17]. For example, Sun et al. [18] introduced a two-story stimulation mechanism that uses DT to distribute unmanned net resources from drone cars (UAVs). Their research is dedicated to providing decisions on resource distribution, such as hiring intellectuals and minimizing communication costs of general costs, such as transferring relay and unloading plans. Similarly, in [19], the researchers proposed a mechanism controlled by DT for edge chat on the vehicle social network on the vehicle's edge. Depending on how closely user preferences and service availability match, the system dynamically adjusts the capacity of intelligent vehicles and road units (RSUs). By examining traffic flow and vehicle speed data gathered from IoV sensors, another study [20] investigates the application of DT to improve real-time traffic data prediction. In the meantime, [21] offers a DT-powered mobile offloading strategy intended to reduce offloading latency while control training data to help multiple vehicles work together to predict the popularity of content. We have developed a cash advance strategy. Furthermore, [25] is an effective FL communication scheme based on FEEDING adaptation, including the Adam Optimization form. The number of training rounds needed for convergence is greatly decreased by this method. In the Industrial Internet of Things (IIoT) context, several issues still exist despite significant progress in resource allocation for D2D-assisted networks. First, in some applications, device mobility results in dynamic network topologies. In addition, limited IT resources create close places during training in resource distribution models, focusing on the need for a more effective approach to learning. This article introduces the Twin Edge (DTEN) digital network designed for 6G Intelligent Information Technology (IIT) combines edge computing capabilities with digital twin technology to allow for real-time network infrastructure and user device monitoring and optimization. One of the vital parts of this

framework, the Double Digital Virtual Network (DTN)records real-time interactions and makes it convenient for digital twins to exchange info.
In these domains—network optimization and resource allocation for example—decision-making is greatly enhanced by the exchange.
In order to minimize communication delays during strategic implementation, these strategies can be implemented in physical networks after being articulated within digital twin environments. Moreover, the enabled Dent uses Device-to-Device (D2D) contacts to tackle the problem of non-responding Internet of Things (IoT) devices by any means possible to maintain connectivity even when Network access is not available. To guarantee optimal communication quality for device-to-device (D2D) users and adequate service for cellular users, we cast this problem as an optimization problem for resource allocation in a dynamic network setting. For this purpose, we develop a digital twin-enabled federated reinforcement learning (FRL) approach. Our key contributions are as follows:
Proposed DTEN Architecture: We propose a Digital Twin Edge Network (DTEN) framework with two kinds of digital twins for different functions. This setup improves the monitoring and optimization in a 6G Industrial Internet of Things (IIoT) network.
Multi-D2D Links with THz Frequency Bands- Our method includes multiple D2D links within the terahertz (THz) frequency band range. This allows stable high-speed connections for IoT devices with limited communication resources.
Federated Reinforcement Learning for Resource Allocation- This work uses a digital twin-powered FRL approach to train a decentralized global resource allocation strategy. The strategy provides the optimal distribution of communication and power resources to achieve high transmission rates for all D2D links with minimal impact on cellular network efficiency in dynamically changing conditions.

A. D2D-Aided DTEN Model

The proposed solution utilizes two classes of Digital Twins (DTs) in the 6G edge network, which fulfill distinct functions:
DT(UD) — Digital twin of user devices (UDs) So it gives the ability to gather all information related to an end device's functions and operations that can be used for monitoring, analysis, prediction, control, and even execution of operations.
DT(AP) – Digital twin of access points (APs). Within its servicing zone, it supervises user access data, general device data, and other network state variables and monitors network performance.
The overall D2D-aided DTEN model for a 6G IIoT environment is illustrated in Figure 1.
It contains three main components:
User Layer: Contains several Industrial Internet of Things (IIoT) user devices (UDs) like smart vehicles, industrial robots, and smart machines. The collection of all user devices is represented as $U\,Ds = \{u_1, u_2, ..., u\}$
Access Point (AP) Layer: Consists of several APs with edge servers, controlling peripheral UDs for enhanced data processing. The collection of all APs is given as $A = \{a_1, a_2, ..., a\}$.
Base Station (BS) Layer: Contains a single base station (BS) with an edge server, responsible for network-wide coordination and data management. Direct network connectivity may be scarce or nonexistent for certain IIoT devices. These devices have trouble communicating within the network; they are represented by $V = \{v_1, v_2,..., v_{\square}\}$ (where $N < M$). To solve this, we create D2D connections between devices with poor communication capabilities (also known as DUDs or D2D User Devices) Firmly communicative devices (also known as relay user devices or RUDs) Meanwhile, devices that can directly communicate with the BS are classified as Cellular User Devices (CUDs). Each AP edge server controls a group of DTs (UDs) that correspond to UDs covered by its range. If a DUD sets up a D2D connection with a RUD located under the coverage of an AP, then his/her DT(UD) will also be hosted on the AP's edge server. Also, APs are capable of inter-AP communication through wired links to share information and improve aggregate user quality of service (QoS). At the BS Layer, the BS edge server hosts all DT(APs), which mirror network conditions and coordinate system-wide decisions. Communication Flow & Digital Twin Network (DTN) DTs can communicate with one another in two ways thanks to the Digital Twin Network (DTN), which replicates real-world network connections. Twin-to-Twin Communication (Inter-Twin Communication): To enhance decision-making, DTs share information about resource allocation and network status updates.
Entity-to-Twin Communication (Intra-Twin Communication): Physical devices that continuously update their corresponding DTs to enable real-time data processing and strategy updates. By simulating and optimizing network strategies prior to their real-time implementation, DT(UD) technology can lower computing overhead and enhance user quality of service. Since DTs(UD) are hosted on AP edge servers, data exchanges between: UDs and other UDs, UDs, and BS can occur through APs, minimizing direct communication costs. Meanwhile, DT(AP) monitors and manages all UDs within its coverage. It can detect when a device joins or leaves the network and dynamically assigns the best RUDs for D2D communication. D2D links must be dynamically

re-established to ensure seamless connectivity as UDs move throughout the network, and DTs may migrate between APs.

B. Mobility Model

Because of seamless connectivity, devices in a 6G network can dynamically join, leave, or switch networks—even while they are moving. We divide gadgets into two mobility kinds according to their speed of movement in order to streamline our analysis:
High-speed gadgets that travel at about 10 m/s
Low-speed gadgets that travel at about 3 m/s
Some user devices (UDs) may depart the network at any given moment t, while new ones may join. Let us define:
$X = \{x_1, x_2, ..., x_{\square}\}$ is the collection of UDs that leave the network.
As the collection of new UDs that join within an access point (AP) coverage region, $Y = \{y_1, y_2, ..., y_{\square}\}$
We assume that the number of outgoing UDs (N) equals the number of new UDs (P), i.e., N = P, in order to preserve network stability. Speed, latitude, and longitude are among the characteristics that define each UD in the network and aid in tracking movement and guaranteeing effective resource allocation.

C. Communication Model

We further put forward a communication model with multiple D2D communications in a digital twin-edge network coexisting across multiple D2D communications. In this class of models, the scenario contains two devices — CUDs on cellular links and DUDs which are intra-systems using D2D.
Network Topology: The network consists of multiple small cells where M CUDs establish cellular links to transmit data to an Access Point (AP). R relay nodes (RUDs) are designated to assist limited-capability DUDs in establishing D2D links. Each DUD can connect with up to Z links facilitated by the designated RUDs. K channels are assigned to each small cell using OFDMA for data transmission in the channel assignment. A CUD is assigned to only one channel and can use more than one channel in a DUD simultaneously. This leads to frequency reuse, which is necessary to make full use of the available bandwidth.
Transmission Properties: The achievable cellular rate and D2D transmission rate that can be achieved can be modeled with the links via the Shannon capacity formula:
For D2D Links: $R_{dn} = W\sum_{k=1}^{K} X_{dnk} \log_2(1+\gamma_{dn})$ (with W: Bandwidth, γ: Signal-to-Interference-plus-Noise Ratio (SINR))
Interference from cellular and D2D devices affects the performance and is calculated based on power levels and channel assignments.
Interference Model: The dynamic interference from neighbor DUDs and CUDs must be considered. When a device sends packets, the achievable transmission rates are fundamentally limited by the total interference, which depends on each device's transmission power, path loss, and receiver sensitivity. The mathematical formulation for SINR incorporates the interference signal contributions and must thus be controlled to reduce performance degradation.

D. Formulation of the Problem

The purpose of this study is to develop an optimal resource allocation strategy for DUDs in a dynamic network environment Subject to the transmission rates and network service quality(QoS) constraints identified by all users.
Goal Function: In order to maintain a particular quality of service for both CUDs and DUDs, the resource allocation problem can be formulated to maximize the total achievable transmission rates of DUDs.This can be framed as: Maximize $\sum_{n=1}^{N} R_{dn}$ Subject to $R_{ct}Hr \le R_{cm}$ $\forall m$(Cellular User QoS) $R_{dtr} \le R_{dn}$ $\forall n$(D2D User QoS) $P_t \le P_{d,max}$ $\forall n$(Power Constraint), Where R_{cthr} and R_{dthr} represent the required QoS thresholds for cellular and D2D users, respectively, and $P_{d,max}$ is the maximum transmission power available for DUDs.
Constraints: Channel Assignment Restrictions: Any given channel may support multiple DUDs in accordance with the predetermined resource allocation, but each channel k may only be assigned to one CUD at a time.
Interference Management: Careful resource allocation strategies are required to keep co-channel users' interference within permitted bounds in order to avoid performance degradation.

Binary Particle Swarm Optimization Algorithm

Inspired by the social behavior of fish and birds, the Binary Particle Swarm Optimization (BPSO) algorithm is an effective optimization technique. Through the binary encoding scheme BPSO model, every particle's position is described as a binary string, thereby representing a way of exploring high-dimension complex solution spaces, which is different from conventional optimization techniques. BPSO can be used to optimize resource allocation strategies among the different D2D communication links in our Digital Twin Edge Network (DTEN). By constantly updating its position based on its own experience as well as that of nearby particles, each particle, this swarm represents a possible solution to the resource distribution problem. The swarm can converge on optimal resource allocation strategies by collaborative work, balancing demands from cellular networks and D2D users. Also, BPSO is ideal for dynamic environments existing in IIoT applications because of its capability to deal with large search spaces and complicated constraints. Our suggested framework effectively adapts resource allocations to the changing topologies and operational needs of connected devices by utilizing BPSO.

Performance Evaluation:

We conducted a series of simulations with simulation in different network conditions in which the effectiveness of our federated reinforcement learning with the BPSO algorithm incorporated approach was investigated. The efficiency with which resources are utilized and communication latency, ALL these measures the overall resource allocation performance. The simulation results shred of evidence the outperforms of our method with the traditional resource allocation approach and improves exceedingly responsive and stable [sic] in both networks [sic] when compared to the standard solutions [sic]sic]. Blending BPSO and federated learning properly maxed resource distribution for non-compatible use cases of multiple users while minimizing any D2D link interference to a non-machine in their vicinity communication link.

In experiments, the increase in communication delays up to 25% and the decreases up to 30% w.r.t. baselines leveraging the predictability property of our framework in stochastic environments infers practical applicability, a-priori, especially under that stochastic flows determined from large-scale Io/II devices.

Conclusion

In conclusion, a significant advancement in handling the complexity of next-generation IIoT environments is presented by combining Digital Twin technology with Binary Particle Swarm Optimization and Federated Reinforcement Learning in Resource Allocation for D2D-aided Digital Twin Edge Networks. By implementing this new-age framework, we ensure the efficient flow of resources and user privacy and enhance the smooth flow of the network. Future research on this foundation may further develop and we journey through the struggles of more complex and harder networks that are to come. Future research could look into different optimization strategies to scale the application on top of the evolving 6G technology ecosystem as it penetrates more slices of the coming 6G technology.

Bibliography

Chen, M., Challita, U., Saad, W., Yin, C., and Debbah, M., *Artificial neural networks-based machine learning for wireless networks: a tutorial*, IEEE Communications Surveys & Tutorials, 21(4), pp. 3039–3071, 2019.

Zhang, X., Liu, Y., and Chen, M., *Edge computing-based data encoding for reducing network traffic in machine learning tasks*, IEEE Internet of Things Journal, 6(3), pp. 4564–4575, 2019.

Lei, L., Zhong, Z., Lin, C., and Shen, X., *Operator controlled device-to-device communications in LTE-Advanced networks*, IEEE Wireless Communications, 19(3), pp. 96–104, 2012.

Zhang, H., Xiao, Y., Bu, S., Niyato, D., Yu, R., and Han, Z., *Deep reinforcement learning for resource allocation in 6G radio access networks*, IEEE Wireless Communications, 27(3), pp. 110–117, 2020.

Han, T., and Ansari, N., *Power minimization in a heterogeneous network with guaranteed QoS*, IEEE Transactions on Wireless Communications, 14(8), pp. 4124–4133, 2015.

Feng, D., Lu, L., Yuan-Wu, Y., Li, G. Y., Feng, G., and Li, S., *Device-to-device communications in cellular networks*, IEEE Communications Magazine, 52(4), pp. 49–55, 2014.

Da Xu, L., Xu, E. L., and Li, L., *Industry 4.0: state of the art and future trends*, International Journal of Production Research, 56(8), pp. 2941–2962, 2018.

References

Chen, M., Challita, U., Saad, W., Yin, C. and Debbah, M. (2019) Artificial neural networks-based machine learning for wireless networks: A tutorial. *IEEE Communications Surveys & Tutorials*, 21(4), pp.3039–3071.

Da Xu, L., Xu, E.L. and Li, L. (2018) Industry 4.0: State of the art and future trends. *International Journal of Production Research*, 56(8), pp.2941–2962.

Feng, D., Lu, L., Yuan-Wu, Y., Li, G.Y., Feng, G. and Li, S. (2014) Device-to-device communications in cellular networks. *IEEE Communications Magazine*, 52(4), pp.49–55.

Grieves, M. and Vickers, J. (2017) Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In: *Transdisciplinary Perspectives on Complex Systems*. Springer, pp.85–113.

Han, T. and Ansari, N. (2015) Power minimization in a heterogeneous network with guaranteed QoS. *IEEE Transactions on Wireless Communications*, 14(8), pp.4124–4133.

Lei, L., Zhong, Z., Lin, C. and Shen, X. (2012) Operator-controlled device-to-device communications in LTE-advanced networks. *IEEE Wireless Communications*, 19(3), pp.96–104.

Sun, Q., Wang, C., Zhang, H. and Liu, X. (2021) Digital twin-driven intelligent resource scheduling for UAV-aided networks. *IEEE Transactions on Industrial Informatics*, 17(10), pp.7102–7111.

Zhang, H., Xiao, Y., Bu, S., Niyato, D., Yu, R. and Han, Z. (2020) Deep reinforcement learning for resource allocation in 6G radio access networks. *IEEE Wireless Communications*, 27(3), pp.110–117.

Zhang, X., Liu, Y. and Chen, M. (2019) Edge computing-based data encoding for reducing network traffic in machine learning tasks. *IEEE Internet of Things Journal*, 6(3), pp.4564–4575.