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ARTICLE

Efficient Digital Twin Placement for Blockchain-Empowered Wireless Computing Power Network

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ABSTRACT

As an open network architecture, Wireless Computing Power Networks (WCPN) pose new challenges for achieving efficient and secure resource management in networks, because of issues such as insecure communication channels and untrusted device terminals. Blockchain, as a shared, immutable distributed ledger, provides a secure resource management solution for WCPN. However, integrating blockchain into WCPN faces challenges like device heterogeneity, monitoring communication states, and dynamic network nature. Whereas Digital Twins (DT) can accurately maintain digital models of physical entities through real-time data updates and self-learning, enabling continuous optimization of WCPN, improving synchronization performance, ensuring real-time accuracy, and supporting smooth operation of WCPN services. In this paper, we propose a DT for blockchain-empowered WCPN architecture that guarantees real-time data transmission between physical entities and digital models. We adopt an enumeration-based optimal placement algorithm (EOPA) and an improved simulated annealing-based near-optimal placement algorithm (ISAPA) to achieve minimum average DT synchronization latency under the constraint of DT error. Numerical results show that the proposed solution in this paper outperforms benchmarks in terms of average synchronization latency.

KEYWORDS

Wireless computing power network; blockchain; digital twin placement; minimum synchronization latency

1 Introduction

Wireless services like holographic communication and intelligent interaction are increasingly data and computing intensive, posing challenges to current computing networks [1]. To meet the demand for real-time immersive user experiences, researchers are exploring new computing architectures, such as the Wireless Computing Power Network (WCPN). WCPN is an integrated intelligent system that delivers intense and adaptive computing services by effectively utilizing resources from diverse devices [2]. It seamlessly integrates communication, computing, and networking across edge nodes, clouds, and terminal nodes, allowing users to access comprehensive computing services on demand. Through edge-to-edge interaction, WCPN identifies distributed computing power and resources for automatic optimization and service scheduling. However, wireless computing networks, being open architectures, face challenges in efficient and secure resource management in WCPN due to issues like insecure communication channels and untrusted device terminals.

Blockchain, serving as a shared, immutable distributed ledger, offers a distributed and secure resource management solution for WCPN [3]. Using smart contracts on the blockchain enables code to execute tasks and manage node registration, task allocation, and reward distribution in the wireless computational power network. Smart contracts ensure transparent task execution, fair reward distribution, and enhance trust [4]. Blockchain technology establishes decentralized identity and trust systems, allowing traceability of transactions to individual participants, reducing fraud, and enhancing security [5]. Cryptocurrencies and smart contracts provide rewards and incentives, encouraging active participation in network management and operation. However, in the process of empowering WCPN with blockchain, efficient resource management encounters challenges such as device heterogeneity, difficulty in monitoring communication states, and the dynamic nature of networks [6].

As a bridge between reality and virtuality, Digital Twin (DT) can provide a digital representation that accurately reflects the physical entities for WCPN [7]. Based on real-time data streams, physical models, and historical data, DT can ensure data synchronization between the physical entities and digital models, and eventually form a digital, intelligent, and informationized digital representation. To achieve high-fidelity data synchronization in the WCPN, Cao et al. [8] investigated the short-packet structure optimization to keep information fresh in the industrial 6G network. Han et al. [9] proposed a game-based dynamic hierarchical framework for IoT-assisted optimal DT synchronization. Mobile edge computing is the backbone of WCPN. It allocates computing power to the network edge for data processing. Combined with DT, it can make decisions faster and reduce response time and latency. Therefore, the DT for blockchain-empowered WCPN is a promising method to ensure users enjoy high fidelity and low latency services.

The placement of DT has a significant impact on data synchronization between the physical entities and digital models, different deployment strategies often come with different latency and issues [10]. Recently, some existing works have explored the DT placement problem preliminary. In [11], considering the data age constraint, the authors proposed a DT placement problem that minimizes the maximum request-response latency. Chukhno et al. [12] addressed the placement of DTs with social capabilities by accounting for network detail and social peculiarities. Although existing works provide precious insights into the DT deployment problem, these works have not considered the DT synchronization delay and DT error in the data synchronization process between the physical entities and digital models. To ensure the users enjoy a high-quality service provided by WCPN, how to deploy DT optimally is a problem worth exploring.

WCPN necessitates the realization of real-time transmission of high-definition video across the network, as well as precise positioning of virtual objects within the actual environment, thus offering users a novel face-to-face experience. This environment leverages contextual information pertaining to the given scene, which may not be readily accessible in the present actual scenario. Given these considerations, we design a DT for blockchain-empowered WCPN architecture and define the essential optimization problems in WCPN. To further reduce the DT synchronization latency under the DT error constraint, we design an improved simulated annealing-based algorithm to achieve a near-optimal DT placement strategy. The main contributions of this paper are summarized as follows:

1) In order to ensure precisely capture the real-time data synchronization demands of users, we first design an architecture of the DT for blockchain-empowered WCPN. Then, we introduce an essential optimization problem for DT placement, which considers DT synchronization

latency and DT error. This is crucial in guiding the design and improving the performance of WCPN and has great potential for various application scenarios.

2) To solve the DT placement problem, we introduce an enumeration-based optimal placement algorithm (EOPA) that enumerates all placement cases to accurately select the optimal placement. However, EOPA has very high computational complexity as the scale of the network increases. We adopt an improved simulated annealing-based near-optimal placement algorithm (ISAPA) to obtain a near-optimal placement with lower computational complexity. ISAPA is a more effective solution to achieve a near-optimal placement compared to the famous K-medians clustering placement algorithm (KMPA).
3) We demonstrate through extensive online real-world topologies to verify the performances of the proposed algorithms. Experimental results show that for all topologies and DT number settings, ISAPA gets a close performance to the EOPA with a small running time.

The remainder of this paper is organized as follows. Section 2 presents the related work. Section 3 explains the system model, which illustrates the network architecture and formulates the placement problem, etc. Section 4 provides a detailed elaboration and analysis of two distinct layout solutions. Section 5 showcases simulation results aimed at validating the efficacy of the two layout algorithms and illustrating the runtime reduction in synchronization latency across varying numbers of DT servers. The article is concluded in Section 6.

2 Related Work

Blockchain technology has gained significant attention in the WCPN, especially in the emerging 5G era. The widespread deployment and ultra-short distance transmission characteristics of 5G provide substantial advantages for user-centric applications. Blockchain is seen as a promising solution for decentralized security and automated execution in the WCPN. Multiple frameworks have been proposed to integrate blockchain with computing networks to leverage these benefits. For example, Wang et al. [3] introduced a novel approach to federated learning in the WCPN, using blockchain technology to ensure provable security and decentralization. Nodes have the flexibility to join or leave the federated training process within the WCPN without facing authorization barriers or security vulnerabilities. Huang et al. [13] presented a DAG-structured blockchain designed for data sharing to improve system throughput. Similarly, Zhao et al. [14] proposed a consortium blockchain system aimed at building user trust and protecting vehicle privacy in the message announcement process. Wang et al. [15] introduced an enhanced Merkle tree structure designed for streamlined transaction verification within secure blockchain-enabled IIoT systems. Their study initially scrutinized the existing construction methods and verification mechanisms of the Merkle tree structure. Subsequently, the authors devised an optimized version of the Merkle tree structure, detailing its construction and verification processes. Nguyen et al. [16] introduced a novel approach for safeguarding CPS in the healthcare domain through secure intrusion detection and blockchain-mediated data transmission coupled with a classification model. Their methodology leverages blockchain technology to ensure the secure transmission of data to cloud servers. Subsequently, a residual network (ResNet) based classification model is employed at the cloud server end to discern the existence of diseases. However, current blockchain systems heavily depend on user or terminal interactions, which presents significant scalability and capacity challenges in large-scale WCPN environments.

Digital twins, as an emerging technology that combines virtuality and reality, provide new approaches for solving these problems. Physical objects in the real world can be synchronized in real-time with their digital representations through DT, providing users with a more realistic and comprehensive experience. In recent years, there has been an increasing number of research on digital twins for WCPN. Qi et al. [17] developed a real-time video analysis model based on DT, which achieves real-time monitoring and analysis of video content through digital twin technology, providing technical support for video networking. Liu et al. [18] proposed a digital twin technology based on multi camera visual data fusion for the application of DT in WCPN, to achieve integrated analysis and intelligent decision support of multi-source video data. Hu et al. [19] designed an intelligent video recommendation system for WCPN, which achieved personalized video recommendation and content distribution optimization by DT modeling of user behavior data and video content. However, current research mainly focuses on digital twin modeling and application algorithm optimization, neglecting the importance of digital twin placement strategy. The placement of DT should fully consider environmental characteristics and participant needs, not only balancing system performance and data security, but also considering resource utilization efficiency.

In order to improve the rationality of resource allocation during the deployment of digital twins, some researchers have explored and optimized the placement strategy of digital twins. Hadjidemetriou et al. [20] proposed an intelligent building energy consumption optimization method based on DT placement strategy, modeling energy consumption and optimizing energy allocation and scheduling strategies. Kasi et al. [21] established a DT placement mechanism in industrial manufacturing to monitor production lines in real time, optimizing equipment layout and production scheduling for improved efficiency. Zhou et al. [22] established a secure data distribution and access control mechanism for DT placement to address data security issues and protect participant privacy. Min et al. [23] developed a DT placement strategy to optimize resource utilization efficiency, optimizing node deployment and link configuration schemes for improved communication quality. The above work focuses on searching for the optimal solution for placement DT that better meets practical needs. However, this is often a complex optimization problem, and they overlook the computational complexity that comes with increasing network scale, which requires a lot of computing resources and time to determine the optimal solution.

As a metaheuristic optimization algorithm, simulated annealing avoids local optima by accepting inferior solutions and ultimately finds the global optimal solution. This characteristic makes simulated annealing highly effective in complex placement strategy optimization problems. Zhu et al. [24] proposed a method of optimizing sensor node layout using a simulated annealing algorithm in the Internet of Things environment to maximize network coverage and data collection efficiency. Bi et al. [25] studied the application of a simulated annealing algorithm in edge computing and improved the performance and efficiency of edge computing networks by optimizing task allocation and resource utilization. Nidhya et al. [26] implemented the optimal placement strategy in large-scale sensor networks through a simulated annealing algorithm to maximize network coverage and communication quality. Haseeb et al. [27] also explored the application of a simulated annealing algorithm in vehicle networking to optimize the deployment of vehicle nodes and improve network connectivity and data transmission efficiency. These studies indicate that simulated annealing algorithms have broad application prospects and potential in placement optimization problems in large-scale network scenarios.

In this work, our focal point revolves around augmenting the reliability and expeditious data transmission capabilities inherent within the blockchain-empowered WCPN paradigm. Our overarching objectives encompass the reduction of DT synchronization latency and the meticulous consideration of DT error, thereby amplifying the efficiency of blockchain-empowered WCPN systems. Furthermore, we endeavor to devise algorithms with significantly lower computational complexities, facilitating seamless integration into large-scale network environments of blockchain-empowered WCPN.

3 System Model

In this section, we introduce a new architecture that integrates digital twin functionality into the blockchain-empowered WCPN paradigm, thereby enhancing its effectiveness and scope. Our discussion mainly revolves around the problem of DT placement, where we addressed the necessity of synchronizing DT instances while adhering to strict error constraints. Through detailed elaboration, we emphasize the importance of reducing DT synchronization delay within the prescribed error threshold framework.

3.1 Architecture of Digital Twin for Blockchain-Empowered Wireless Computing Power Network

The schematic of DT for the blockchain-empowered WCPN framework is depicted in Fig. 1. The inherent nature of WCPN presents a challenge in establishing a universal public blockchain system to oversee terminals globally. As terminal-centric applications, such as data sharing, primarily involve nearby terminals, there arises no necessity for blockchain nodes across the entire network for transaction verification and consensus processes. Therefore, we have devised a framework comprising multiple subsystems, each dedicated to managing data and terminals within specific WCPN contexts. In WCPN, the complete framework comprises three key components: a physical layer, a virtual layer, and a blockchain system. DT servers play a crucial role in establishing DTs for cloud servers and overseeing the blockchain system within the virtual environment. The reciprocal data exchanges among cloud servers are encapsulated as cyber-transactions, denoted as $T = \theta_i, d_i, t_0$, facilitated by corresponding DT servers. Here, d_i represents the account address of the DT for the cloud server, t_0 represents timestamp, while θ_i signifies the DT modeling information, encompassing the interaction type and digital signature transmitted. Through the attainment of a virtual consensus mechanism among DTs of cloud servers, the transaction T is duly recorded in the blockchain ledger. In WCPN, we adopt DPOS (Delegated Proof of Stake) as our consensus mechanism. The decision to use DPOS in WCPN is based on several factors. Firstly, DPOS is highly efficient, rapidly achieving network consensus, thereby improving throughput and performance. Secondly, compared to other mechanisms like PoW (Proof of Work), DPOS consumes less energy, crucial for resource-constrained nodes in mobile and wireless computing networks.

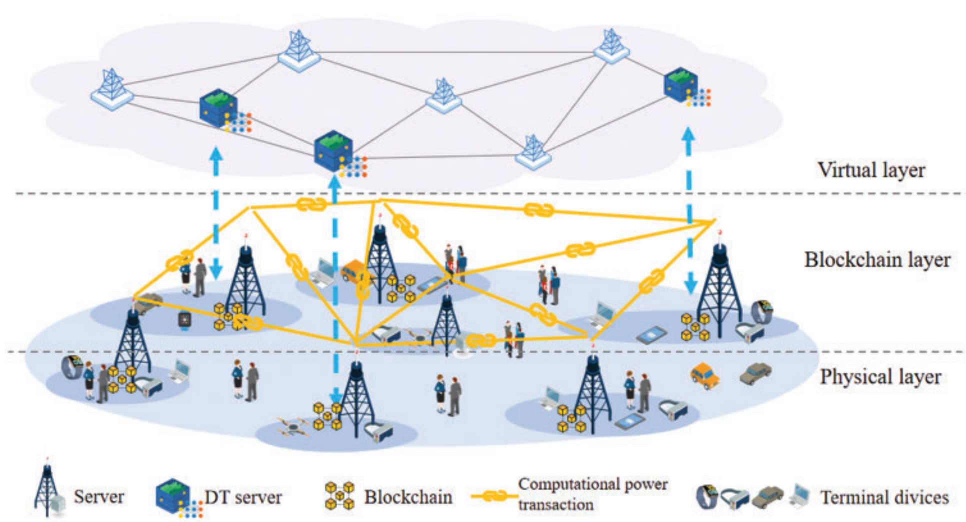


Figure 1: An architecture of DT for the blockchain-empowered WCPN network

The physical layer includes a large number of terminal devices, WCPN cloud servers, and DT servers. Terminal devices include various smart endpoints, including but not limited to smartphones, computers, and smartwatches, all of which meet the necessary performance standards for seamless integration in the WCPN ecosystem. In addition, with the continuous advancement of technology, professional terminals are expected to become a key component of the WCPN field. These terminal devices are combined with WCPN infrastructure through various technologies, such as multiple sensors, mobile graphics processing units (GPUs), and touch screens. The processing of massive data in the field of the Internet of Things (IoT) is mainly driven by cloud servers, which constitute the core of WCPN services. By utilizing cloud computing capabilities, these servers rely on high-speed physical links to establish connections, provide network services, and achieve resource sharing between terminals. In addition, they also provide important data processing and computational support, including 3D modeling, which helps to provide services tailored to user needs. The DT server is located within the physical layer and is responsible for maintaining the DT representation of physical entities hosted by the cloud server. These servers play a crucial role in obtaining real-time status updates of physical entities, ensuring the fidelity of the DT model. The strategic deployment of DT servers on selected cloud servers is an essential component to ensure the synchronization and accuracy of DT representations in the WCPN architecture.

In the blockchain layer, each cloud server providing computational capability deploys a local blockchain DT replica, with these replicas synchronized through consensus mechanisms such as Delegated Proof of Stake (DPoS). Some lightweight devices can deploy only partial blockchain data and rely on full nodes for transaction verification and block data retrieval when necessary. This deployment ensures the decentralized and distributed nature of the network, while guaranteeing data consistency and security. Blockchain leverages smart contract technology for automated resource scheduling, facilitating dynamic allocation of computational resources and ensuring adherence to service rules. This approach not only enhances resource utilization efficiency but also guarantees fairness and reliability of services. Most importantly, the immutability and traceability of the blockchain ensure that all computational and resource interactions are reliably recorded. This capability allows everyone to audit interactions at any time, enhancing network transparency and trustworthiness, thereby further elevating the overall performance and availability of the entire network.

The virtual layer assumes a pivotal role in the WCPN system, with an important aspect being the DT modeling of physical entities. This layer is dedicated to detailed modeling and simulation of cloud servers, which helps create virtual representations that correspond to the actual environment. Through the digitization described by cloud servers, the network layer strives to encapsulate and reflect their behavior, status, and inherent characteristics, thereby achieving seamless real-time data transmission and synchronization. This ability promotes remote monitoring, analysis, and operational control of entities, enhancing the overall effectiveness of the WCPN system. The DT modeling process not only deepens the understanding of the physical environment, but also lays the foundation for a series of applications such as decision support, optimization, and predictive analysis in WCPN systems. In addition, the task of the network layer is to utilize complex algorithms, strategies, and artificial intelligence (AI) technologies to deeply study the depth of data processing, analysis, and mining. This multifaceted approach is essential for extracting key information and supporting the provision of advanced services within the WCPN ecosystem.

3.2 Digital Twin Placement

In the DT for blockchain-empowered WCPN network architecture, the data synchronization process from cloud servers to DT servers is crucial. This complex process requires transmitting the processed computational output and real-time status updates of physical entities from the cloud server to the DT server. Subsequently, the DT server carefully maintains the digital twin representation of the corresponding cloud server and provides relevant feedback based on the observed changes in the physical entity state. Therefore, the strategic layout of DT servers is intricately intertwined with the performance optimization of DT for blockchain-empowered WCPN networks. In order to make wise use of DT server resources and avoid resource misallocation, an orderly approach was adopted, in which a subset of cloud servers was carefully selected as the deployment site for DT servers.

DT placement strategies may involve selecting which DT servers to store data on to ensure its security and reliability. This entails choosing appropriate DT nodes within the WCPN to ensure data confidentiality, integrity, and availability. Meanwhile, DT synchronization errors may lead to data inconsistency and unreliability. This meticulous selection process is based on a comprehensive evaluation of various factors, including DT error, calculation of workload distribution, and delay considerations. By wisely selecting the location of DT servers, the overall goal is to improve the efficiency, reliability, and scalability of the DT for blockchain-empowered WCPN network, thereby enhancing the performance and functionality of the entire ecosystem. The DT for blockchain-empowered WCPN network is modeled by an undirected graph G(V, E), where $\boldsymbol{V} = \{i, i = 1, 2, \ldots, |\boldsymbol{V}|\}$ is the set of all cloud servers, and $\boldsymbol{E}$ is the set of the high-speed physical link between the cloud servers. We define that k DT servers, $\boldsymbol{S} = \{j, j = 1, 2, \ldots, k\} \subset \boldsymbol{V}$, are deployed on the DT for blockchain-empowered WCPN network to be co-located with cloud servers. For ease of description, some key notations are listed in Table 1.

Table 1: Notation setting

Notation	Meaning
$\mathbf{V}$	The set of all cloud servers
$\boldsymbol{E}$	The set of the high-speed physical link between the cloud servers
r	The propagation rate of the physical link
$d(i, j)$	The shortest path distance between cloud server i and DT server j
α	The probability coefficient
β	The packet loss rate at each cloud server during the data synchronization phase
$h_{i,j}$	The hops of the shortest path between the cloud server i and DT server j
L_{ave}	The average DT synchronization latency
ε_{max}	The maximum threshold of DT error
$\mathcal{L}_{i,j}$	The synchronization latency
$\varepsilon_{i,j}$	The DT error

3.3 DT Synchronization Latency and DT Error

As the expected improvement in performance within the blockchain-empowered WCPN network, it is characterized by strict requirements for ultra-low latency and ultra-high reliability, and it is necessary for each cloud server to synchronize data with the DT server in the least amount of time. The inherent time lag in data transmission between these entities is a key determinant of user satisfaction in high fidelity and low latency service delivery in the WCPN paradigm. Therefore, minimizing the latency between cloud servers and DT servers is crucial for meeting strict performance benchmarks required by blockchain-empowered WCPN applications.

In assessing the congruence between the DT and its physical counterpart, we propose the concept of DT synchronization latency. This latency denotes the delay in data transmission between the DT model and the corresponding edge server to which it is mapped. However, the DT synchronization latency is mainly determined by the distance between the cloud server and the DT server. Hence, the synchronization latency $\mathcal{L}_{i,j}$ between the cloud server i and DT server j is defined as

$$\mathcal{L}_{i,j} = \frac{d(i,j)}{r}, i \in \boldsymbol{V}, j \in \boldsymbol{S}, \tag{1}$$

where r denotes the propagation rate of the physical link, $d(i,j)$ represents the shortest path distance between cloud server i and DT server j, $\boldsymbol{V}$ and $\boldsymbol{S}$ denote the set of cloud servers, set of DT server, respectively.

Meanwhile, in the context of our research, we introduced the concept of DT error as a quantitative measure aimed at evaluating the fidelity and accuracy of DT representations. This indicator can be used to quantify the differences between digital twin models and their corresponding physical models. In fact, the occurrence of DT errors mainly stems from packet loss events that occur during the data synchronization phase between cloud servers and DT servers within the WCPN framework [28]. Given the stringent demands for accuracy inherent within WCPN environments, it becomes imperative to establish a threshold for acceptable DT error. By delineating this threshold, our study endeavors to establish a benchmark against which the efficacy of data synchronization processes can be evaluated. Such precision-driven benchmarks are instrumental in guiding the optimization efforts aimed at mitigating DT error and enhancing the overall reliability and fidelity of the WCPN network. The DT error can be given as

$$\varepsilon_{i,j} = \alpha(1 - (1 - \beta)^{h_{i,j}}), i \in \boldsymbol{V}, j \in \boldsymbol{S}, \tag{2}$$

where α denotes the probability coefficient, β represents the packet loss rate at each cloud server during the data synchronization phase, $h_{i,j}$ denotes the hops of the shortest path between the cloud server i and DT server j.

4 Digital Twin Placement for Latency Minimization

In this section, we delve into the intricate problem of DT placement, taking into account two critical factors: DT synchronization delay and DT error. Our objective is to minimize DT synchronization latency, thereby enhancing the overall performance of the system. To achieve this goal, we propose the Enumeration-based Optimal Placement Algorithm (EOPA), which effectively identifies the optimal DT placement with high accuracy. Additionally, we leverage the Improved Simulated Annealing-based Near-optimal Placement Algorithm (ISAPA) that excels in its superior efficacy in attaining a near-optimal DT placement solution.

4.1 Problem Formulation

Within the operational framework of DT for blockchain-empowered WCPN network, each DT server plays a crucial role in maintaining a digital representation corresponding to the cloud server, while providing real-time feedback based on observed state changes within physical entities. Driven by the overall goal of strictly adhering to strict DT error constraints and minimizing average DT synchronization latency, strategic deployment decisions related to k DT servers across different cloud server infrastructures have become crucial. This allocation will affect user satisfaction with the low latency and high fidelity services provided by WCPN.

Therefore, we define the placement problem for k DT servers, which is to find the placement for k DT servers to minimize the average DT synchronization latency L_{ave} under the constraints of Eqs. (3a)–(3c). This optimization problem is formulated as follows:

$$\min \frac{1}{|\mathrm{V}|} \sum\nolimits_{i \in V} \sum\nolimits_{j \in \boldsymbol{S}} \mathcal{L}_{i,j} \tag{3}$$

$$\text{s.t.} \sum\nolimits_{j \in \boldsymbol{S}} I_{i,j} = 1, \forall i \in \boldsymbol{V} \tag{3a}$$

$$\varepsilon_{i,j} \leq \varepsilon_{max}, \forall i \in \boldsymbol{V}, \forall j \in \boldsymbol{S} \tag{3b}$$

$$I_{i,j} = \{0, 1\}, \forall i \in \boldsymbol{V}, \forall j \in \boldsymbol{S}, \tag{3c}$$

where $I_{i,j}$ is the indicator variable which represents whether the DT server j maintains the DT of cloud server i. If DT server j maintains the DT of cloud server i, variable $I_{i,j} = 1$, otherwise, $I_{i,j} = 0$. Constraint (3a) represents that the DT of each cloud server only be mapped to one DT server, and ε_{max} denotes the maximum threshold of DT error. Constraint (3c) outlines the integrality requirements for the indicator variables.

4.2 An Enumeration-Based Optimal Placement Algorithm

We first enumerate all possible placement schemes for k DT servers. Then, it is necessary to calculate the minimum average synchronization latency for each scheme. In our work, calculating the minimum average synchronization latency for each scheme relies on Dijkstra algorithm in the shortest path algorithm, which finds the shortest path in weighted graphs. Here, the weights represent synchronization latency between nodes, and the shortest path denotes the network's minimum synchronization latency. Based on Dijkstra algorithm, we calculate the average DT synchronization latency among all placement schemes and update the minimum average DT synchronization latency L_{ave} under the constraint of the maximum DT error. Finally, we obtain the optimal placement case, according to the comparison of the average synchronization latency among all placement cases.

The objective of the optimal placement solution is to determine the placement scenario $\boldsymbol{S'} = \{I_{i,j}, \forall i \in \boldsymbol{V}, \forall j \in \boldsymbol{S}\}$ from the set $\mathbf{A}$, $\mathbf{A}$ represents all potential placements of k DT servers. The aim is to achieve the lowest average synchronization latency for data synchronization. This solution involves: 1) considering all feasible placement scenarios for k DT servers, and 2) assessing the average synchronization latency for each placement scenario. The selection of the $\boldsymbol{S'}$ by remote cloud in the WCPN network is based on minimizing the average synchronization latency while adhering to the constraints outlined in Eqs. (3a)–(3c). The details of EOPA can be found in Algorithm 1.

Algorithm 1: An Enumeration-based Optimal Placement Algorithm (EOPA)

Input:
G($\boldsymbol{V}, \boldsymbol{E}$), k, ε_{max}
Output:
Final placement set $\boldsymbol{S}_{opt}$ for DT servers, the minimum average DT synchronization latency $\mathcal{L}_{min}$
1: **Initialize** the set of all placement cases of k DT servers $\boldsymbol{S}_k \leftarrow \varnothing$ and the minimum DT synchronization latency $\mathcal{L}_{min} \leftarrow +\infty$

(Continued)

Algorithm 1 (continued)

Enumerate all placement cases of k DT servers in $\boldsymbol{V}$, and record all cases into set $\boldsymbol{S}_k$.
for $\boldsymbol{S}' \subset \boldsymbol{S}_k$ **do**
  calculate the DT synchronization lateney $\mathcal{L}_{ave}$ and the DT error $\varepsilon_{i,j}$
  if $\mathcal{L}_{min} > \mathcal{L}_{ave}$ **and** $\varepsilon_{i,j} < \varepsilon_{max}$ **then**
    update $\mathcal{L}_{min} \leftarrow \mathcal{L}_{ave}$, update $\boldsymbol{S}_{opt} \leftarrow \boldsymbol{S}_{opt} \cup \{\boldsymbol{S}'\}$
  end if
end for
return $\boldsymbol{S}_{opt}, \mathcal{L}_{min}$

Proposition 1. The computational complexity of Algorithm 1 for EOPA is $\mathrm{O}\left(\frac{|\mathbf{V}|!}{k! \cdot (|\mathbf{V}| - k)!}\right)$.

Proof: The computational complexity of Algorithm 1 involves two main components: 1) the enumeration of all combinations of placing k DT servers among the set of $|\mathbf{V}|$ cloud servers, and 2) the assessment of $\mathcal{L}_{ave}$ for each placement scenario $\boldsymbol{S}'$. Specifically, the time complexity for enumerating all potential placements is $\mathrm{O}(\mathrm{C}_{|\mathbf{V}|}^{k})$. According to the calculation rule of combination number, it's also recorded as $\mathrm{O}\left(\frac{|\mathbf{V}|!}{k! \cdot (|\mathbf{V}| - k)!}\right)$. The computational complexity for evaluating $\mathcal{L}_{ave}$ per placement scenario $\boldsymbol{S}'$ is $\mathrm{O}(k \cdot |\mathbf{V}|^2)$. By merging the evaluation times for all placements, the overall computational complexity of Algorithm 1 is $\mathrm{O}\left(\frac{|\mathbf{V}|!}{k! \cdot (|\mathbf{V}| - k)!}\right)$.

4.3 An Improved Simulated Annealing-Based Near-Optimal Placement Algorithm

In the above, EOPA enumerates all placement cases to select the optimal placement but it has very high computational complexity with the scale of the network increases. In the research on solving DT placement problem, methods such as Particle Swarm Optimization Algorithm and Whale Optimization Algorithm are also actively being explored. However, although these algorithms reduce computational complexity compared to EOPA, challenges such as slow convergence speed and difficulty in moving away from local optima may arise.

Simulated Annealing (SA) algorithm is a global optimization method inspired by the natural process of solid annealing [29]. At high temperatures, the internal particles of a solid exhibit a fast and disordered state due to their considerable internal energy. As the temperature decreases gradually, the energy within the solid diminishes, leading to a gradual transition towards a more ordered state. Ultimately, as the solid reaches room temperature, its internal energy reaches a minimum value, and the particles achieve their most stable configuration. The Simulated Annealing algorithm emulates this annealing process to identify the optimal solution for the given problem. This approach offers a probability of escaping local optimal solutions in favor of the global optimum.

In this section, an improved simulated annealing algorithm is adopted to solve the problem of digital twin placement. The improved simulated annealing algorithm has a memory function and sets a parameter that can accept the maximum number of non optimal solutions. It not only ensures accuracy, but also reduces running time and improves search efficiency.

The following outlines the primary steps of ISAPA: First, randomly select an initial set of DT servers as the optimal placement $\boldsymbol{S}_{opt}$ and calculate the average synchronization latency as the minimum latency $\mathcal{L}_{min}$. Then in the while loop, if the count of accepting poor performance solutions *num* is lower than the maximum num_{max}, then generate a new neighbor solution $\boldsymbol{S}_{new}$, and calculate the new average synchronization latency $\mathcal{L}_{new}$ and DT error ε. If the new neighbor solution is lower than the minimum latency, i.e., $\mathcal{L}_{new} < \mathcal{L}_{min}$, we update the local optimal set $\boldsymbol{S}'$, and record the $\boldsymbol{S}'$ into $\boldsymbol{S}_{opt}$ as the optimal solution and reset $num = 0$. If the acceptance probability $\mathrm{P}(\Delta) = \mathrm{e}^{-\frac{\Delta}{\gamma}}$ is larger than a random number $\gamma (0 < \gamma < 1)$, it indicates that we have the probability to accept a poor performance solution and update $num = num + 1$. Repeat the above process until num exceeds the maximum count of accepting poor performance solutions num_{max}. Finally, we reduce the temperature slowly and update the optimal solution $\boldsymbol{S}_{opt}$ and $\mathcal{L}_{min}$ until the temperature drops to the terminate temperature $\boldsymbol{T}_{final}$. The details of ISAPA can be found in Algorithm 2.

Algorithm 2: An Improved Simulated Annealing-based near-optimal Placement Algorithm (ISAPA)

Input:
$\mathrm{G}(\boldsymbol{V}, \boldsymbol{E})$, k, ε_{max}
Output:
Final placement set $\boldsymbol{S}_{opt}$ for DT servers, the minimum average DT synchronization latency $\mathcal{L}_{min}$

Initialize $\boldsymbol{T}_0$, $\boldsymbol{T}_{final}$, num, num_{max}, the annealing coefficient ρ
Select randomly k nodes from $\boldsymbol{V}$ as the initial set of DT servers $\boldsymbol{S}_{opt}$
Calculate the average synchronization latency $\mathcal{L}_{min}$
while $\boldsymbol{T} > \boldsymbol{T}_{final}$ **do**
    if $num < num_{max}$ **then**
        generate new neighbor solution of DT servers placement $\boldsymbol{S}_{new}$
        calculate the average synchronization latency $\mathcal{L}_{new}$, and DT error $\varepsilon_{i,j}$
        $\Delta = \mathcal{L}_{new} - \mathcal{L}_{min}$
        generate a random $\gamma \in (0, 1)$
        if $\Delta < 0$ **then**
            $\boldsymbol{S}' = \boldsymbol{S}_{new}, \boldsymbol{S}_{opt} = \boldsymbol{S}', \mathcal{L}' = \mathcal{L}_{new}, \mathcal{L}_{min} = \mathcal{L}', num = 0$
        else if $\mathrm{e}^{-\frac{\Delta}{\gamma}} > \gamma$ **then**
            $\boldsymbol{S}' = \boldsymbol{S}_{new}, \mathcal{L}' = \mathcal{L}_{new}, num = num + 1$
        end if
    end if
    $\boldsymbol{T} = \rho \cdot \boldsymbol{T}$
    if $\mathcal{L}' < \mathcal{L}_{min}$ **and** $\varepsilon_{i,j} < \varepsilon_{max}$ **then**
        $\mathcal{L}_{min} = \mathcal{L}', \boldsymbol{S}_{opt} = \boldsymbol{S}'$
    end if
end while
return $\boldsymbol{S}_{opt}$, $\mathcal{L}_{min}$

Proposition 2. The computational complexity of Algorithm 2 for ISAPA is $\mathrm{O}(k \cdot |\mathbf{V}|)$.

Proof: The time complexity of ISAPA mainly depends on the size of the problem, including the number of cloud servers $|\mathbf{V}|$ and the number of DT servers k. For other operations in the ISAPA algorithm, their time complexity is at a constant level and can be ignored. Therefore, the overall computational complexity of Algorithm 2 can be expressed as $\mathrm{O}(k \cdot |\mathbf{V}|)$. The various operations in the algorithm have efficient computational performance, ensuring the overall efficiency and practicality of the algorithm.

5 Performance Evaluation

In this section, we evaluate the performance of the proposed EOPA and ISAPA algorithms. In addition, we adopt a random placement algorithm (RANDS) and KMPA as benchmarks.

5.1 Simulation Settings

We created a Python simulator to analyze how various DT placements affect synchronization latency in the WCPN network. To evaluate the performance of the algorithms and ensure generality, we took the real-world online network topologies from the Topology Zoo [30] for DT for blockchain-empowered WCPN network computing architecture, i.e., TLex, Agis, and GTS-IP. This is a collection of annotated network diagrams from public network maps, used to deploy DT servers to cloud servers. Topology Zoo is a resource used for studying and comparing computer network topology. It provides a variety of network topology samples aimed at helping researchers better understand the structure, performance, and behavior of networks. this "Zoo" is borrowed from biology, drawing an analogy between network topology and the diverse species found in the animal kingdom. The topology samples in Topology Zoo cover networks of various scales, shapes, and features, ranging from small-scale local area networks to large-scale Internet backbone networks. In particular, Table 2 lists the details of three network topologies. In this paper, all simulations are implemented in Python 3.8 running on a PC with double 3.30 GHz CPUs, 8.00 GB RAM, and Windows 10 operating system.

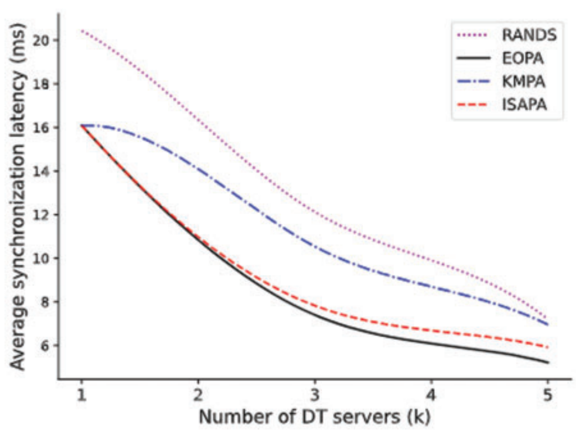
Table 2: Topology settings

Topology	Number of nodes	Number of edges
TLex	12	20
Agis	23	33
GTS-I	37	58

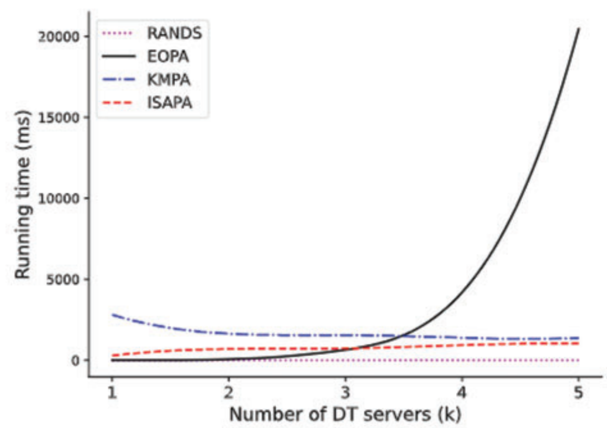
In this experiment, the random placement algorithm (RANDS), K-media clustering placement algorithm (KMPA) [31], and enumeration based placement algorithm (EOPA) were used as comparative experiments to further verify the superiority of the proposed method (ISAPA). For the RANDS, a placement scheme is generated by cycling 1000 times and the average synchronization delay is calculated. Finally, the placement scheme corresponding to the minimum average synchronization delay is obtained. In the enumeration based placement algorithm, all possible placement schemes for k digital twin servers are first listed. The average synchronization delay of all placement schemes is calculated based on the shortest path algorithm, and the minimum average synchronization delay is continuously updated under the constraint of maximum error. Finally, by comparing the average synchronization delay of all placement algorithms, the optimal placement strategy is obtained.

5.2 DT Servers Placement for Latency Minimization

Fig. 2 illustrates the performance obtained by RANDS, EOPA, KMPA and ISAPA as a function of the number of DT servers. Fig. 2a shows that the average synchronization latency of four algorithms with the number of DT servers increasing from 1 to 5. The latency decreases as the DT server count rises due to reduced cloud server-DT server distances. EOPA employs iterative calculations to determine the optimal placement scheme, while ISAPA consistently delivers results that closely align with the optimal scheme as the number of DT servers increases. On the other hand, RANDS' reliance on random exploration results in the highest latency outcomes. Although KMPA performs better than RANDS, it falls short of the efficiency achieved by ISAPA as the quantity of DT servers expands. Overall, ISAPA excels in achieving an approximate optimal solution, demonstrating superior performance in comparison to KMPA. Fig. 2b depicts the comparison of the running time among these algorithms. Specifically, the computational complexity of EOPA is the highest. Because the EOPA must compute the average synchronization latency of all possible placement cases to select the optimal placement strategy. With the number of DT servers increasing, more placement cases that need to be calculated, lead to a surge in EOPA running time. However, the running time of KMPA decreases with the increase of DT servers, but it is still higher than ISAPA and RANDS in the range of DT servers. In addition, as the number of DT servers increases, the running time of ISAPA and RANDS is the closest.



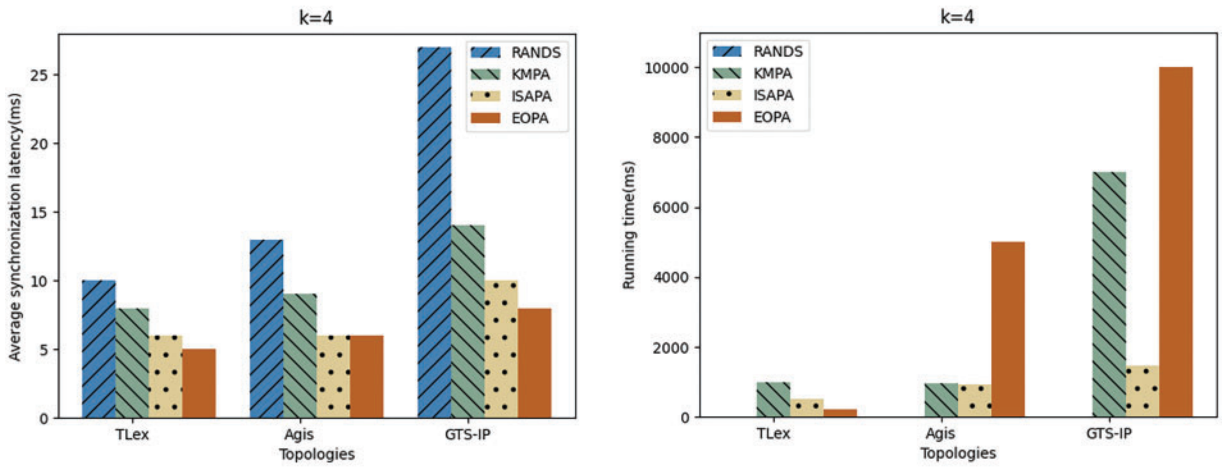
(a)



(b)

Figure 2: Performance of RANDS, EOPA, KMPA and ISAPA in Agis Topology Networks. (a) Comparisons of average synchronization delay under the different numbers of DT servers. (b) Comparisons of running time under the different number of DT servers

In order to further verify that ISAPA provides a near-optimal solution to the DT placement problem in different topology networks, we place four DT servers to compare the running time and average synchronization latency among TLex, Agis, and GTS-IP topology networks. Fig. 3a shows the trend of average synchronization latency under different algorithms with the complexity of the network topology increases. We can see that ISAPA can obtain a near-optimal solution compared to EOPA, which is even better than KMPA. Moreover, RANDS has a bad performance of average synchronization latency regardless of the network topology scale. In summary, ISAPA can achieve a near-optimal solution in a smaller running time. As illustrated in Fig. 3b, we noticed that RANDS has the smallest running time, regardless of the network size. As the complexity of the network topology increases, the running time of EOPA and KMPA increases apparently. On the contrary, the running time of ISAPA shows the slowest growth with the number of nodes and edges increasing.



(a) (b)

Figure 3: Comparison of average synchronization latency and running time and of TLex, Agis and GTS-IP topology Networks. (a) Comparisons of average synchronization latency under the different topology Networks. (b) Comparisons of running time under the different topology Networks

5.3 DT Servers Placement for DT Error

Fig. 4 shows the comparison of the average DT error among RANDS, EOPA, KMPA, and ISAPA. The average DT error decreases as the number of DT servers increases. RANDS consistently has higher DT errors than EOPA, KMPA, and ISAPA due to its lack of consideration for DT synchronization latency and error from randomness. KMPA's clustering approach reduces error compared to RANDS but is not optimal. ISAPA, utilizing an improved simulated annealing algorithm, considers multiple factors for comprehensive DT placement evaluation. The average DT error of ISAPA proposed in the paper is very close to that of the EOPA algorithm. Although the variation of DT error is small, even small errors can have a significant impact in some high-precision scenarios. Therefore, timely and accurate information is crucial for making wise decisions.

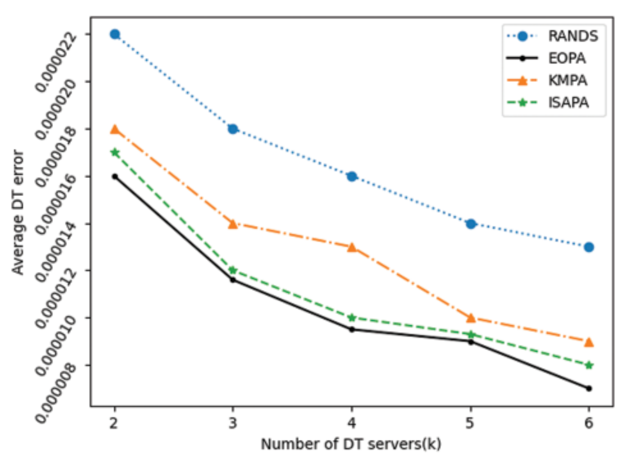


Figure 4: Comparisons of average DT error under the different number of DT servers

Based on the experimental analysis conducted, it has been observed that EOPA achieves an optimal solution to the DT placement problem. However, its practical implementation is hindered by the excessively high computational complexity involved. In contrast, ISAPA showcases superior efficiency and manages to secure a near-optimal solution while maintaining lower computational complexity in the resolution of such problems.

6 Conclusion

In this article, we first proposed a DT for blockchain-empowered WCPN network architecture to satisfy the synchronization requirements of high-reliability and low latency services provided by WCPN. We discussed the DT placement to minimize average synchronization latency under the constraint of DT error. Based on this, we proposed the EOPA and ISAPA algorithms as the solution for the DT placement problem and simulated the situation of different networks using three different online network scales. Experiments have shown that ISAPA achieves near-optimal performance and has low computational complexity compared to the EOPA, KMPA, and RANDS. Therefore, ISAPA is a potential solution to address DT placement in the DT for blockchain-empowered WCPN network. In the future, we will consider dynamic scenarios of DT construction and deployment issues. The main challenge lies in adapting quickly to the dynamic demands, which undoubtedly poses a significant challenge in blockchain-empowered WCPN.

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Availability of Data and Materials: Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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