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A Digital Twin (DT) approach to Narrow-Band Internet of Things (NB-IoT) wireless communication optimization in an industrial scenario

Muhammad Dangana *, Sajjad Hussain, Shuja Ansari, Muhammad Imran, Ahmed Zoha

University of Glasgow (UofG), James Watt School of Engineering, Glasgow, G12 8QQ, Scotland, UK

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ABSTRACT

The pervasive realization of virtual replication of physical entities termed Digital Twin (DT) has been utilized in this paper to optimize the wireless communication of the Narrowband Internet of Things (NB-IoT) in an industrial scenario. This optimization is exclusively achieved through DT approach. NB-IoT is a Low-Powered Wide Area Network (LPWAN) standardized by 3GPP and leverages Long Term Evolution (LTE) technology. The Amplify-and-Forward (AF) optimization technique is used to improve the performance of some notably poor-performing terminals in the scenario. Bit-Error-Rate (BER) tests show the terminals' overall performance before and after optimization. An improvement of 17% is achieved in BER. The signal quality of the channels is analyzed as well as the Cumulative Distribution Function (CDF) is used to showcase the effective throughput performance of the NB-IoT terminals.

1. Introduction

Recent convergences of several computational techniques and technologies have led to advancements in the application of DT in numerous disciplines [1]. Subsequently, wireless communication networks have experienced rapid growth, and with the advent of 5G and the Internet of Things (IoT), wireless communication has become the driving force for Industry 4.0, smart cities, agricultural industries, and public infrastructure monitoring [2]. While continuous efforts are being made to resolve the challenges faced by wireless communication, our approach to optimize wireless communication using DT has emerged as a promising area of research to resolve some of the challenges associated with wireless communication in complex scenarios.

A DT refers to a virtual representation of physical systems, processes, or devices that allows for real-time monitoring, analysis, and even control of these entities [3]. From the perspective of wireless communications, DT can provide a comprehensive and accurate model of a communication network [4], including its components – devices that constitute the network, topology – virtual arrangement of these devices, and behavior — how the system behaves to predefined settings and actions. This practice allows network engineers to simulate and analyze the network's performance and identify potential challenges before they even occur in a real or physical scenario.

* Corresponding author.
E-mail address: m.dangana.1@research.gla.ac.uk (M. Dangana).

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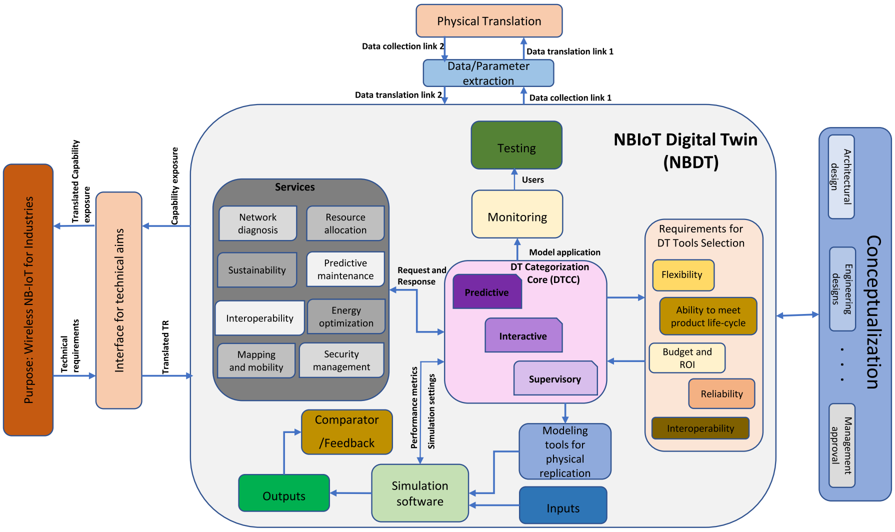

Fig. 1. Digital Twin architectural steps for the implementation of Wireless NB-IoT for industrial use.

Optimization of wireless communication involves designing wireless networks that transmit data efficiently and effectively while meeting a variety of performance metrics, including throughput, bit-error rate, reliability, and energy efficiency. Through the simulation of wireless networks and the analysis of their performance under a variety of scenarios, DT technology can play a critical role in optimizing wireless communication. Wireless communication optimization can therefore benefit from the use of DT, as it reduces the need for extensive physical testing, and facilitates the evaluation of multiple scenarios, resulting in a more rapid optimization process. Our scenario uses a pre-DT, which involves a virtual replication of an intended physical entity as described in [5]. To evaluate the performance of the communication system under various conditions, the DT is connected to a simulated wireless network. As part of the DT wireless communication optimization process, amplify-and-forward optimization algorithms are used in order to determine the optimal configuration of the wireless network that meets specific performance requirements. A wide range of applications for wireless communication optimization can also be found in Industry 4.0 [6] that rely on NB-IoT connectivity, which can be used to design wireless networks capable of enabling reliable and efficient communication between machines, sensors, and other devices.

This paper focuses on optimizing the wireless communication of NB-IoT through the utilization of DT technology. A DT industrial environment was established, employing DT architectural steps illustrated in Fig. 1. The implementation process was facilitated through the proficient utilization of modeling and simulation tools, namely CATIA, SketchUp, Wireless Insite, and MATLAB. The judicious selection of these tools was informed by their alignment with the predefined criteria articulated in Section 4, specifically about the evolution of the system and DT tools requirements.

The chosen tools exhibit commendable features such as re-calibration and re-configuration capabilities, which are pivotal for accommodating the dynamic parameters in the process of the DT creation - (Evolution of the system). Noteworthy among their attributes is a demonstrated track record of delivering optimal data and outcomes over an extended period. These tools, individually tailored to address distinct aspects of the research, collectively contribute to the comprehensive methodology.

CATIA was instrumental in modeling certain industrial equipment, providing a detailed representation of their structural intricacies. SketchUp (free 3D warehouse), on the other hand, was adept at capturing the spatial dimensions and architectural nuances of the industrial structures under investigation. Wireless Insite, a specialized tool, took center stage in modeling the NB-IoT wireless communication network, ensuring a nuanced exploration of its intricate dynamics. Finally, MATLAB played a pivotal role in data aggregation and visualization, lending its analytical prowess to distill meaningful insights from the amassed information.

In synthesizing the functionalities of these tools, the implementation process attains a nuanced and multifaceted approach, fortified by the specialized capabilities each tool brings to the fore. The DT environment facilitated the observation and monitoring of the transmission and signal propagation patterns of 25 NB-IoT terminals. The performance of these terminals was assessed in terms of key wireless communication parameters, including distance, bit-error rate, throughput, signal-to-interference plus noise ratio, and cumulative distribution function. The simulation process illustrated the wireless behavior of NB-IoT terminals communicating with the NB-IoT tower as depicted in Figs. 2 and 3. Identified poor-performing terminals underwent parameter adjustments, coupled with the introduction of the Amplify-and-Forward (AF) optimization technique. The AF technique was employed within the DT environment to enhance the performance of under-performing NB-IoT terminals, contributing to the general optimization of the NB-IoT wireless communication system. Section 6 presents the detailed results and conclusions drawn from the optimization efforts. The identification and resolution of poor-performing terminals, along with the application of the AF optimization technique, showcase improvements in the overall performance of the NB-IoT wireless communication system.

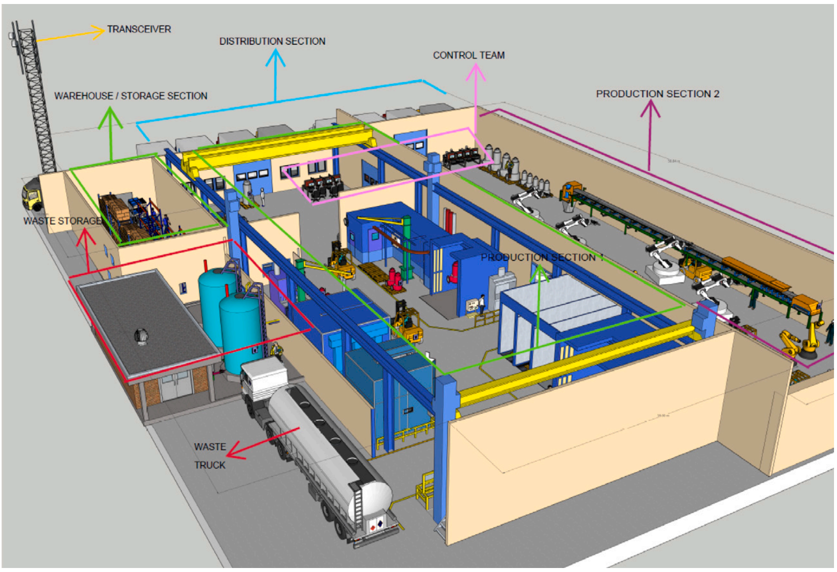

Fig. 2. An Aerial Perspective of the Layout for the Industrial Complex Mapping Out its Multifaceted Sections or Compartments.

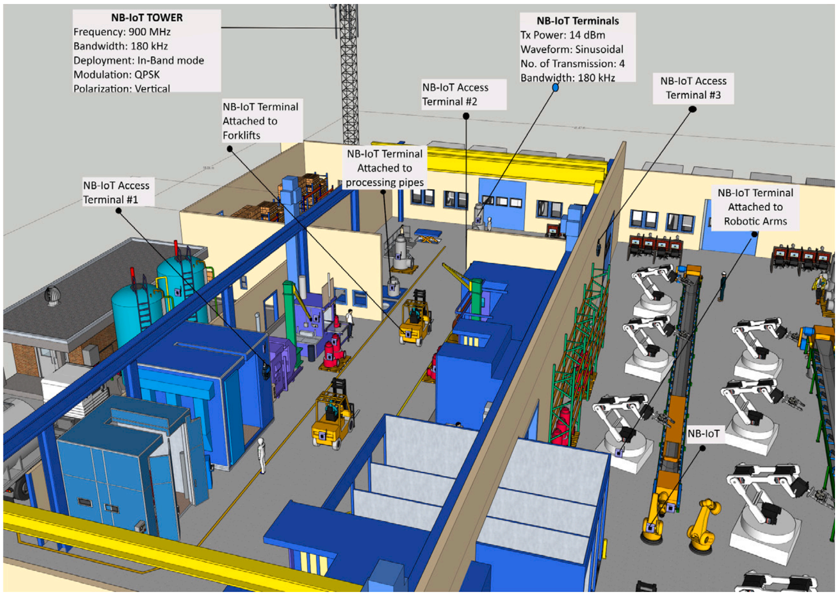

Fig. 3. An Ariel View of the Industrial Complex Showcasing Some of the Positions of the NB-IoT Terminals and Transceiver Tower as well as the Configuration Parameters — the Communication Devices.

The remaining parts of this paper are structured as follows: Section 2 highlighted some of the research works carried out in the field of DT and wireless communication. Section 3 presents the role DT plays in modern Industry 4.0. In Section 4, we delve into the requirements for choosing a suitable DT concerning the optimization of wireless NB-IoT within an industrial context as well as its reliability upon its implementation. Section 5 presents the implementation of the system model as it relates to DT for NB-IoT application. Results obtained from this scenario are presented and discussed in Section 6. In Sections 7 and 8, the paper discusses the challenges it encounters and provides its conclusion, respectively.

2. Related works

Several studies have been carried out on DT. Among them is the investigation and discussion carried out on the unique features of DTs, such as their run-time environment, semantic orientation, and internal structure, resulting in a reference architecture model by [7]. The authors of this study were able to use DT to estimate the effects of the product, procedure, and service outcomes by utilizing virtual models. This is one of the major economic elements of modern industrial enterprises. The authors focused on testing some features of DT while this paper focuses on communication networks using DT. Among other types of DTs that have been discussed by [8] is the simulated DT which uses advanced simulation tools and Machine Learning (ML) technologies to predict the dynamics of a physical system. The authors here used ML to observe the physical structure while this paper looked at network optimization using a similar DT approach. Moreover, authors in [9] utilized an open-source IoT and DT architecture to explore the current state of open-source platforms that can be combined to deliver DT capabilities, including actual data gathering, computer-generated description, analytics, and visualization. Similarly, an architecture and Q-learning technique was developed by [10] to improve the status of IoT in a system. A novel contribution that can be applied to DT.

On the performance of DT in wireless edge networks for industrial IoT environments, authors in [11] attempted to solve the latency problem through Ultra-Reliable and Low Latency Communication (URLLC) Link. The solution consisted of a numerical method for reducing latency. To achieve this, transit power, user association with IoT devices, offloading portions, and the processing rate of users and edge servers were optimized. The authors simulated and compared their proposed iterative algorithm with other benchmark schemes to conclude that their proposed algorithm performed better in latency minimization. In a similar research, authors in [12] optimized wireless sensor network access control and load balancing in an industrial DT scenario. Employing DT technology, the research focused on tree-structured processing for chain formations of generated outliers. This process optimized data transmission paths, main chain heads, and non-chain operations within the industry, utilizing DT calculation formulas to determine the remaining cluster heads in industrial operations. Furthermore, to enable new functionalities in 6G, DT was integrated at the edge network through a proposed wireless DT edge network model. As described in the paper, [13], the authors used Deep Reinforcement Learning (DRL) to resolve the challenge of DT placement and Transfer Learning to address the issue of DT migration. The authors also showed that the proposed solution resulted in a reduction of system cost and an improvement in merger rates for flexible network systems, based on the numerical results obtained. Finally, the authors in [14] used a Machine Learning-based Propagation Loss (MLPL) module to estimate the propagation loss in a wireless network. Essentially, this loss is the sum of two entities, namely, the deterministic path loss and the stochastic fast-fading loss. Using an experimental testbed, the authors tested their work with real network traces and compared the results with those of ns-3's existing propagation loss models. According to the authors, the results obtained can accurately predict the propagation loss of DT wireless networks in real network environments, thereby enabling the creation of DT wireless networks using NS-3.

Upon reviewing the cited research, it becomes evident that the body of literature can be discerned along two distinct dimensions. First, there exists a strand of research focused on the application of DT exclusively for the examination of industrial physical entities, devoid of considerations for a homogeneous communication network. Second, a separate strand concentrates on the optimization of communication networks, divorcing itself from the integration of DT. In light of these findings, the present study seeks to bridge these divergent paths by amalgamating the utilization of DT for the purpose of optimizing a homogeneous wireless communication network. This amalgamation is poised to contribute novel insights and advancements at the intersection of DT and wireless communication optimization, thereby enriching the existing academic discourse on this subject matter.

Moreover, in recent related studies, the increasing interest in employing DT technology in wireless networks, particularly in Industrial IoT has been evident. Nevertheless, it is noteworthy that the utilization of DT in the context of NB-IoT within industrial settings remains a relatively unexplored area. This research, therefore, contributes and represents a novelty in this field by presenting a pioneering approach to applying DT in NB-IoT within an industrial environment.

3. The role of DT in optimizing wireless NB-IoT in industry

The goal of Industry 4.0 cannot be overemphasized as it is a rapidly evolving digital transformation of manufacturing that relies on the use of cyber–physical systems, IoT, and big data analytics. This auto-transformation is becoming a reality with the transformation of its physical entities into virtual ones — DT. In Industry 4.0, this realization has highlighted the importance of DT. The development of DTs is meant to be a tested technology designed to emulate physical systems elements, functions, operations, and dynamics digitally. This is to allow for more control over testing, analysis, prediction, and hazard prevention. More precisely, in order to optimize wireless NB-IoT, digital twins can be used in a variety of ways, including:

- **Monitoring and Diagnostics:** Wireless NB-IoT devices and networks can be monitored and diagnostically assessed using DTs. In order to identify and troubleshoot problems, improve efficiency, and prevent errors, the information obtained from DTs can be utilized for these purposes. In the context of wireless NB-IoT networks, DT serves as a virtual representation of the intended physical industrial settings. Real-life data, encompassing parameters such as signal received power, throughput, and propagation paths are seamlessly integrated into the DT. This integration facilitates the continuous monitoring of this critical information. Notably, the implementation of NB-IoT DT in this paper adheres to the Third Generation Partnership Project (3GPP) release 14 specifications [15]. The comparison of monitored parameters against these specifications enables the diagnosis, detection of faults, and identification of anomalies through root cause analysis within the DT system.
- **Parameter Adjustments:** DTs can be used to enhance the performance of wireless NB-IoT networks. The power consumption of the NB-IoT network devices, routing, and propagation patterns are some of the parameters that can be observed, analyzed, and adjusted in order to achieve optimization.
- **Simulation:** Wireless NB-IoT networks can be simulated using DTs under different industrial conditions. These are conditions that are peculiar to industrial settings as generated through a number of iterations or tests. By using this data, new designs can be tested, evaluation of new technologies can be achieved, and enhancement of the network's safety and security is possible.

In this paper, simulation, and parameter adjustments are focal to its optimization approach. However, the use of DTs in optimizing wireless NB-IoT in Industry 4.0 is still in its early stages, but it has the potential to significantly improve the performance, efficiency, and reliability of wireless networks. To this end, it has become imperative to choose the right type of DT and its reliability towards industrial application has become necessary to underscore its role in optimizing wireless NB-IoT in Industry 4.0.

4. Essential components for constructing a DT for wireless NB-IoT optimization

It was of utmost significance to strategically plan and meticulously choose a suitable DT to optimize wireless NB-IoT within the context of achieving the established goals of this study. One of the steps in this process was to review the documentation of the tools that are currently available and determine whether they are suitable for the purpose of this study. To achieve this, the under-listed five (5) conditions were used as guides for choosing a suitable DT tools; [16,17]:

- **Scope and purpose of the project:** In order to implement DT correctly, it was imperative to understand why it is necessary and what the expected results are. In this way, it is easier to determine what impact the results will have on the state of things. Therefore, in this research, the scope and purpose for selecting this DT was to comprehensively investigate the behavioral nuances of wireless propagation and analyze the communication patterns within an industrial context. This endeavor is imperative due to the dearth of extensive research in this domain. The anticipated results aimed to encompass the observation, identification, and analysis of underperforming NB-IoT terminals, with the ultimate goal of optimizing their performance.
- **Evolution of system:** Choosing a DT that evolves with the life cycle of the intended physical asset is a required feature for consideration. This is because as the physical asset evolves over time, the DT technical calibrations and environmental parameters should be able to support these changes. Regarding this research, the selected DT exhibits the ability for re-calibration in response to adjustments in scenario parameters. This capability was demonstrated through the re-calibration and reconfiguration of the tools and parameters to accommodate the changes that occurred during the restructuring and remodeling phase of the DT, including the communication system analysis.
- **Assistance for virtual threads:** These are communication structures that link the various aspects of a system from conception to decommissioning. It is important for DT to support virtual threads because it increases DT accuracy and simplifies its implementation. The chosen DT in this research is anticipated to uphold the complete life cycle of the envisaged physical entity, having already provided support during its conceptualization phase and, ideally, throughout its subsequent real-life realization stage.
- **Open and federated data structure:** With an open-format data structure, DT can easily be updated, scalable, and extended as new prototypes and datasets become available. In the course of this study, when confronted with a new dataset, the selected DT exhibits scalability in effecting, simulating, and managing these data to yield revised or updated results. Furthermore, aligned with the parameters of this investigation, a centralized and federated data structure was employed in lieu of an open and federated data arrangement. This choice stems from the fact that a centralized format facilitates seamless data updates and scalability. In contrast to an open data structure, there exists no imperative for data dissemination across multiple DTs. This is because multiple DTs do not exist in this case.
- **DT tools requirements:** In order to build a DT that can easily be interacted with and provides accurate data in real-time, understanding the types of software and hardware required for setting it up is essential. The selection of DT tools for this research was conducted following the prerequisites of this study, considering that these instruments possess well-documented histories of delivering precise data and outcomes.

4.1. Reliability of wireless NB-IoT industrial DT

The application of DT in several aspects of physical systems, from smart factories to health and transportation industries, has proven that DT is a reliable technology in some use cases [18]. The extent to which DT is reliable depends on the quality of the data used to create it and the accuracy of the models used to simulate the system. If the data is incomplete or the models are inaccurate, the predictions and simulations provided by the DT may not be reliable. Hence, this study employed comprehensive datasets in conjunction with a highly precise model to achieve a commendable level of accuracy. However, DT in the context of wireless communication of NB-IoT in an industrial setting needs to demonstrate its ability to incorporate many of the reliability challenges posed by the harsh conditions of industrial settings to wireless communication. The ability of DT to account for the physical susceptibility of the wireless network to interrupted operations would make the results obtained from DT more reliable. Therefore, depending on the type of industrial environment in which wireless communication is deployed, this means that DT should be able to account for the resultant effect these harsh conditions will have on the network. Conditions like noise or field interference, magnetic fields and emissions, extreme temperatures, flammable gases, humidity and moisture, shocks and vibrations, and power interference. In addition, there is also communication interference such as channel interference and overload [19], airborne particles, and contaminants. The capability of a DT to capture these realities or dynamics as input data would make the output or results more reliable and acceptable. Therefore, given the proficiency of the employed tools within this study, the primary emphasis resided on assessing the impact of noise level on wireless communication, along with an evaluation of the extent to which the physical structure may impede wireless propagation.

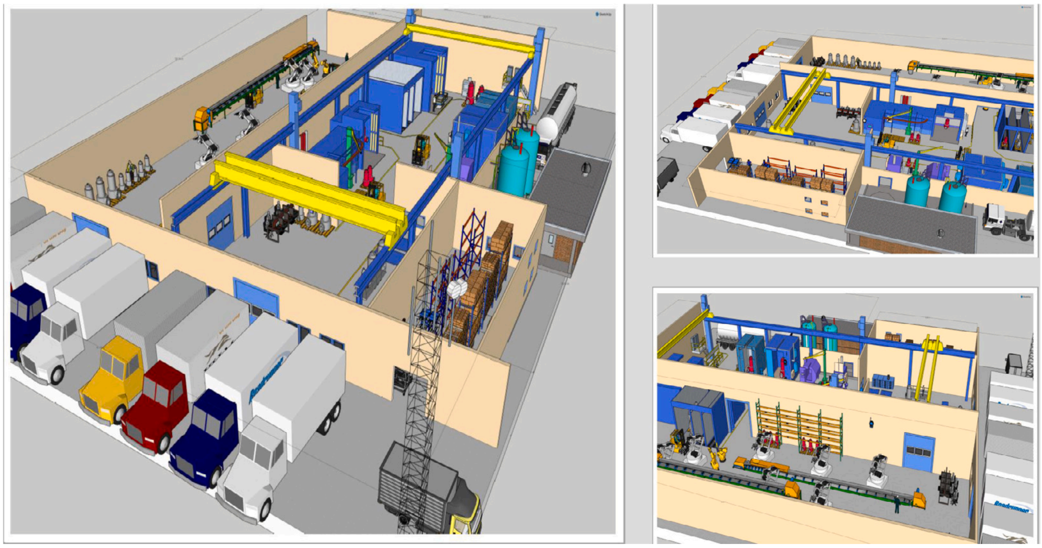

Fig. 4. A three-dimensional view of the pre-DT industrial scenario. A comprehensive view of the twin can be gained from these perspectives. All of the sections of the structure can be seen in this representation, including the NB-IoT terminals, base stations, various types of machinery, robotics, and control teams.

4.2. A description of types of digital twins in industrial indoor NB-IoT

The implementation of DT in the space of wireless communications technology has followed one of the various definitions of applications of DT. This includes virtual replication of systems, services, and processes as it implies the implementation of DT to wireless processes, factories, products, and business services. However, the authors in [5] have illuminated certain categories of DT, providing a comprehensive description of DTs in their diverse forms, which also encompasses futuristic variations as presented below.

- **Pre-DT:** Pre-DT is seen as a form of DT that is a classic virtual paradigm and aimed at developing an initial working project before the physical system is created. This is primarily focused on eliminating or reducing the technical hurdles or threats as well as detecting challenges prior to the design or execution of the main physical entity. An important and specific scenario can be demonstrated using this classic type of DT. Furthermore, it contributes to minimizing technical risks during the initial phases of process design and implementation. Consequently, this study adopted this definition for its implementation.
- **Digital Twin:** This consists of a virtual system model that incorporates performance, health, and maintenance data from a physical counterpart. As a result of the knowledge obtained from digital twins through process iterations, the physical twin can be enhanced in real-time based on the characteristics learned from digital twins. As part of this phase, the digital twin is subjected to a variety of tests in order to determine how the physical twin will respond to various questions. Corrective actions are taken on the physical twin if any deficiencies are identified during the digital twin inspection.
- **Adaptive DT:** This type of DT takes into account the inclination of the operation as well as the priority of the operations. Therefore, this DT takes into account human operational behavior as input to its analytics process. Moreover, the extent to which this DT can be adaptive depends simply on the display or user interface that both the physical and digital twins use.
- **Smart DT:** In addition to its capability, this DT also acquires all adaptive DT features. A machine learning technique is used to generate an unsupervised model that recognizes entities and their relationships in an operational setting. Also, it intelligently predicts and optimizes the degree of accuracy of the conditions and situations in which it observes the environment.

Moreover, other organizations have identified four types of DT based on their functions, benefits, and characteristics. In contrast, others have classified it into three groups according to the phase of the product's lifecycle that is being twinned. This is known as the 3Ps. A brief description of these classifications can be found in [20,21].

5. Implementation of digital twin for NB-IoT application

This section describes the methodological use of DT for the implementation in the wireless section or the transceiver unit of NB-IoT technology. This description follows suit with the regulations and specifications that guide this technology — the 3GPP [15]. The system model is explained to bring forth the methodology or steps involved and the metrics required for the implementation of this DT as it relates to industrial application in an indoor setting. Finally, the implementation of AF as the optimization scheme.

Table 1
Parameters and system assumption values.

Parameters	Values
Bandwidth	200 kHz
Frequency	900 MHz
Transmission rate	6
Reflection rate	10
Diffraction rate	3
Noise Level	>3 dB
UE transmission power	23 dBm
Modulation type	BPSK
FDD deployment mode	Standalone

5.1. Methodology and system model adoption

In this section, the description of a pre-DT [22] scenario for the application of wireless NB-IoT in an industrial setting is provided. A pre-DT is a virtual formulation of a physical asset before it is physically built. This practice allows the iteration of events and parameters to understudy their effect on the assets so that corrections can be made before the physical asset is finally produced. To achieve this, the steps shown in Fig. 1 were adopted. The system was conceived based on the engineering standards and reference scenario as highlighted in [1]. The modeling of the system, as shown in Figs. 2, 3, and 4, consists of an industrial setting that is characterized by various equipment for production, safety, storage, and transportation. Various types of modeling tools were employed to model this industrial scenario as mentioned in Section 1. This modeled scenario has different compartments or sections as specified at the conceptualization stage in Fig. 1. These compartments include production space, warehouse, waste storage, staff office, and control rooms. These sections are clearly shown in Fig. 2. The NB-IoT terminals are attached to the equipment in these various compartments to sense, gather, process, transmit, and receive information wirelessly to a central transceiver point using the 3GPP standards. This central transceiver is the NB-IoT tower as shown in Fig. 3. A total number of 25 NB-IoT terminals were placed in this scenario for this purpose.

NB-IoT is a cellular technology that is Low Power Wide Area Networks (LPWAN) based and utilizes the infrastructure of Long-Term Evolution (LTE). The modules developed for NB-IoT are designed to integrate seamlessly with LTE infrastructure, which is one of the imperative technologies within the IoT. Notably, NB-IoT terminals are equipped with Subscriber Identity Module (SIM) cards issued by a designated telecommunication operator offering specialized NB-IoT services. This strategic integration ensures the efficient utilization of LTE infrastructure, providing a robust foundation for the secure and reliable communication capabilities of NB-IoT modules within the broader landscape of wireless connectivity. These terminals transmit the sensed data to the transceiver or mast as shown in Fig. 3, it is this part of the transmission that has been modeled and simulated in a DT environment using CATIA, SketchUp, and Wireless Insite. The locations of the NB-IoT terminals along with the approximate distances from the terminals to the transceiver are also displayed. This diagram showcases a visual estimation of these distances. This is a direct communication between the terminals and the transceiver. However, in this direct communication, some terminals do not communicate effectively with the transceiver. These terminals are identified in this study and to better their communication, an optimization scheme was employed known as the Amplify-and-Forward (AF) cooperative scheme. As described in Fig. 1, the system uses the parameters in Table 1 for its simulation. The results obtained are fed back into the simulating software for re-simulation through a comparator. This is done for a number of iterations to obtain optimal results. The results obtained via direct communication identified some NB-IoT that performed poorly in communicating with the transceiver point.

In general, DTs are categorized based on application purposes. This categorization as mentioned in [23], includes supervisory, interactive, and predictive DTs. Relating these categorizations as shown in Fig. 1 with the system model adopted in this paper and the type of data generated and collected from the various compartments as shown in Fig. 2, both supervisory and interactive DT is used in this scenario. At the supervisory stage, the DT displays real-time information for human operators. Information provided in this case is useful if people are able to act upon it. As an illustration, by referencing Fig. 2 and directing our attention to the facets pertaining to production and storage, the industrial sector can opt to augment its manufacturing output in response to indications from NB-IoT terminals stationed within the storage or warehousing section, which signal a reduction in the inventory levels. The interactive stage involves the DT automating at least one aspect of a process to improve performance through internal monitoring and complex analysis for better performance. One illustrative instance pertains to NB-IoT terminals tasked with monitoring fluid flow within pipelines. These terminals possess the capability to either initiate or cease the operation of a flow valve, thereby facilitating the regulation of fluid flow. This technology application finds relevance in the context of the waste compartment, as depicted in Fig. 2.

Moreover, a simplified approach to the implementation of the system model is represented in Fig. 5. The services requested are the focal point of the DT testing stage after professional inputs are computed. The results obtained are monitored and compared with those expected. A comparator or a feedback loop is used to keep the output in focus. It is at this stage that several technical risks and design problems are noted and corrected before the physical asset is replicated. When the process reaches a satisfactory stage, data or parameters are extracted for future implementation.

However, it is imperative to acknowledge the existence of a multitude of prerequisites essential for the judicious selection of appropriate tools in the context of DT applications. Despite its apparent simplicity, the process of tool selection can prove to be a

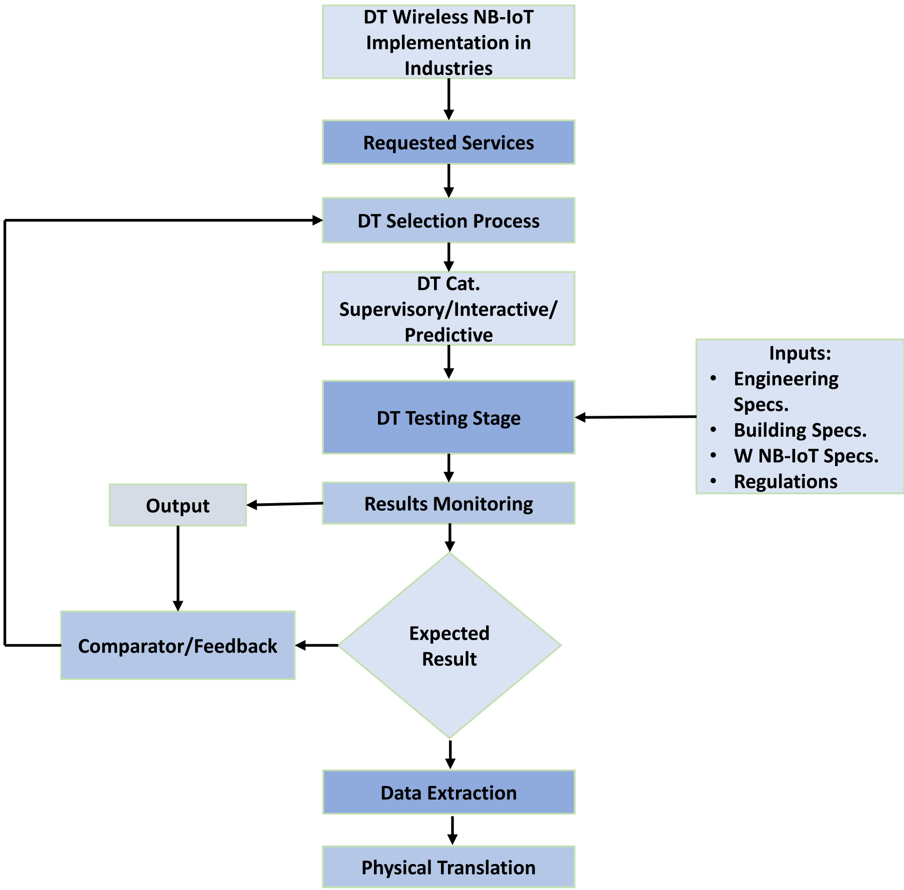

Fig. 5. A simplified presentation of the stages involved in the implementation of a Wireless NB-IoT in an industrial setting.

complex undertaking. However, this complexity can be ameliorated by directing our attention towards the overarching goals and objectives for which the DT is being proposed.

These objectives encompass the evaluation of a selected tool's suitability concerning its versatility of use, compatibility, and integration capabilities with other DTs. This is of paramount significance as, in numerous antecedent DT processes, reliance on a solitary DT software may prove insufficient in furnishing the requisite or ultimate output. The meticulous delineation of these prerequisites is indispensable, as any inadequacy in this regard could engender disharmony within the system, leading to decisions that fail to accurately reflect the true state of the system. It is also imperative that the selection of these tools adheres to the anticipated lifecycle of the system, encompassing essential considerations such as technical support for the chosen tool, periodic updates for enhanced firmware, and vigilance regarding security concerns. In the context of this research, a thorough examination of relevant factors was undertaken, and all necessary prerequisites were satisfactorily fulfilled.

5.2. Optimization of NB-IoT communication in the DT system model

In the context of understanding the wireless behavior of NB-IoT in this scenario with relation to Section 5.1 and Fig. 1, the DT categorization Core (DTCC) determines the type of DT to be selected. DTCC selection is based on the section of the industry from which data is collected via NB-IoT terminals. For example, sensor data from the storage or warehouse section of the industry will prompt supervisory DT settings of the software used in the simulation. These settings serve as an input to the simulator as well as the modeled physical entity and the required service in focus. These required services include network diagnosis, predictive maintenance, resource allocation, interoperability, and sustainability. In the context of this study, the services provided include network diagnosis and predictive maintenance. The testing and monitoring of the process as simplified and depicted in Fig. 5 are carried out within the NBDT. A data collection link 2 provides data input into the system, while a data translation link 1 provides data output. To create a physical entity, this output data is used. Additionally, the technical aim interface facilitates the integration of wireless NB-IoT requirements into the system. The simulator implements its calculations based on specified and established scientific formulations as shown in Eqs. (1) and (2). These calculations rely on the technical parameters provided in Table 1.

Referring to the scenario used in this paper as described in Section 5.1, the results obtained identified some low-performing NB-IoT terminals in terms of their wireless communication abilities. This low-performance results from the direct distance between the NB-IoT terminals and transceivers, obstruction of the wireless signals by industrial equipment, and interference with the signals of interest. Therefore, it is necessary to improve the transmission conditions of these poor-performing terminals to enhance the overall performance of the wireless network. To achieve this objective, an AF technique in a cooperative scheme is employed. This technique uses a cooperative strategy for selecting the most appropriate NB-IoT Access Terminals (NATs) as depicted in Fig. 6 for re-transmission. However, the criteria for choosing the most appropriate NAT are based on the NRT with the highest signal-to-noise ratios (SNRs) for end-to-end communication with the transceiver.

Utilizing an amplification factor, the NAT enhances its received power through the process of normalization, facilitated by block-wise amplification of the transmitted signals. This enhancement is realized subsequent to a rigorous numerical estimation of the channel characteristics.

The term – Gain Used by Relay for Retransmission – refers to the specific gain employed by the NAT to facilitate the process of retransmitting signals. This is illustrated in [[24], Eq. (1)]. In this illustration, the system considers the power level of the transmitted signal.

$$\Gamma = \sqrt{\frac{\alpha}{\left|\mathrm{q}_{\mathrm{t,nat}}\right|^{2}\alpha + 2\beta_{t,nat}^{2}}} \tag{1}$$

where,

Γ = NAT gain and β is derived from [[24], Eq. (2)].

This is obtainable by first considering the transmitted power level at the relay point which is represented by (p_{nat}):

$$G\left[\left|p_{nat}^{2}\right|\right] = G\left[\left|q_{t,nat}\right|^{2}\right] G\left[\left|x_{t}\right|^{2}\right] + G\left[\left|y_{t,nat}\right|^{2}\right] = \left|q_{t,nat}\right|^{2}\alpha + 2\beta_{t,nat}^{2} \tag{2}$$

where t is the transmitting NB-IoT terminal, $\alpha = G\left[\left|x_{t}\right|^{2}\right]$ represent the energy embedded in the transmitting signal. $2\beta_{t,nat}^{2} = G\left[\left|y_{t,nat}\right|^{2}\right]$ represents the summation of the noise power between the transmitter and the receiver while $q_{t,nat}$ is the attenuation experienced in the channel.

Henceforth, this segment undertakes a comprehensive analysis of the ramifications engendered by the proposed scheme upon the operational efficacy of the system. The evaluation entails an in-depth exploration of the Bit-Error-Rate (BER) as well as a rigorous assessment of signal quality, elucidated through the Signal-to-Interference plus Noise Ratio (SINR). The ensuing discussion of these findings is situated within the context of Section 6, facilitating a nuanced and thorough examination of their implications.

5.3. AF cooperative communication scheme for NB-IoT

The integration of Multiple Input Multiple Output (MIMO) antenna technology into miniature sensors or IoT modules presents impractical or unfeasible challenges, with a rare exception as presented by the authors of [25]. This complexity arises from the considerable resource utilization, particularly power consumption. In the context of NB-IoT, the 3GPP specification has prioritized minimizing power consumption to extend service duration and reduce NB-IoT terminal maintenance costs and frequency [26].

In this context, optimizing communication among NB-IoT devices, particularly in demanding environments like industrial indoor scenarios, necessitates the application of a cooperative communication scheme, especially when network homogeneity is of paramount importance. This cooperative communication scheme effectively emulates a virtual MIMO implementation within a predefined operational framework [27].

Within these cooperative communication schemes, NB-IoT terminals collaborate to facilitate the transmission of each other's messages to a designated destination [28].

In furtherance to this scenario, a cooperative communication scheme referred to as AF is employed. In this technique, each NB-IoT terminal within the system receives a noisy signal from a transmitting source, amplifies this signal, and subsequently retransmits it to the base station or transceiver. This process is thoughtfully illustrated in Eqs. (1) and (2). The transceiver, in turn, receives two distinct versions of signals, both exhibiting independent and faded characteristics.

The transceiver employs a signal detection technique to effectively combine these received signals, ultimately yielding a more reliable and informative data stream. It is noteworthy that AF technique, like other cooperative communication schemes, comprises two distinct phases: coordination (phase I) and cooperation (phase II). In the coordination phase (phase I), the NB-IoT terminals engage in the exchange of their source data and control messages. This exchange encompasses communication with other NB-IoT terminals as well as with the base station or transceiver. Subsequently, during phase II, the NB-IoT Access Terminals (NAT) as shown in Fig. 6 collaboratively retransmit the messages they have received to the transceiver, following signal amplification [29]. This cooperative approach enhances the overall robustness and reliability of the system.

6. Results and discussion

In this section, the paper discusses the outcomes observed both before and after implementing the AF cooperative scheme. We delved into key technical factors, including BER, SINR, and the Cumulative Distribution Function (CDF), particularly concerning the system's throughput.

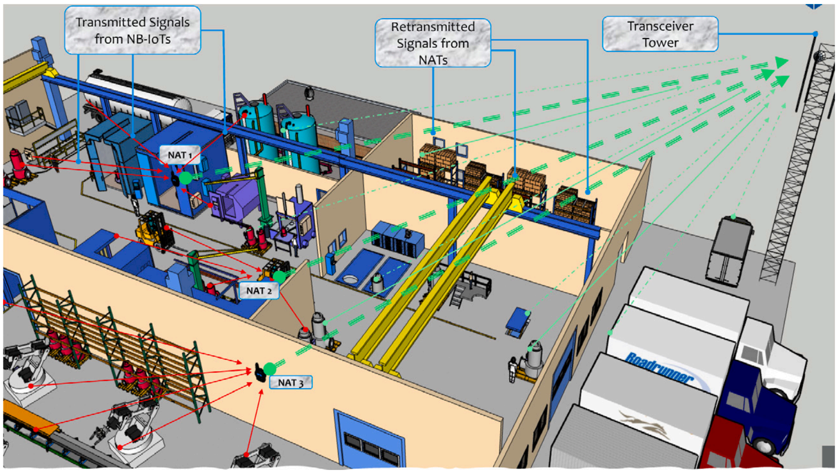

Fig. 6. A depiction of Phase II of the AF scheme. This phase shows the NATs in their cooperative stage after signal amplification.

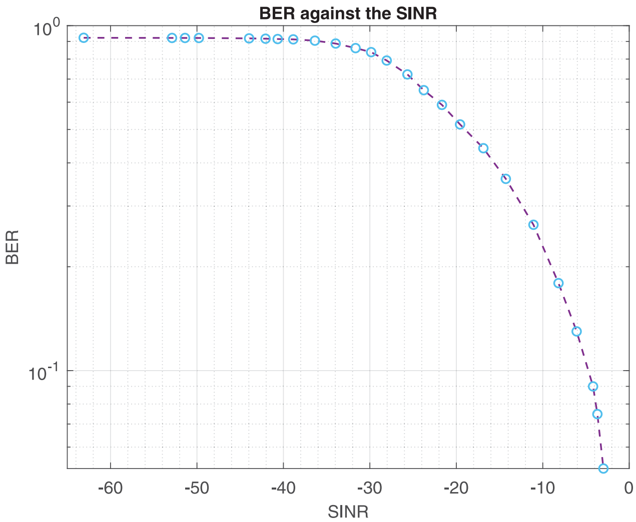

Fig. 7. This is an overview of the BER of the wireless NB-IoT system before the implementation of the AF scheme. The poorly performing terminals have the highest BER as shown.

6.1. *Effect of AF on bit-error-rate (BER)*

An important metric for analyzing wireless communication performance is the average BER. In this scenario, the overall system performance in terms of the number of NB-IoT deployed before the implementation of the AF scheme is presented in Fig. 7. The data was analyzed to understand the performance of NB-IoTs, and certain NB-IoTs were found to have high BER due to some factors. A few of these factors include the reflection of signals caused by equipment composition, low SINR, and distance. Out of the 25 NB-IoT terminals in the scenario, 14 of these were identified for AF scheme implementation. The BER range for these terminals is between 0.7221 and 0.9222. Nevertheless, upon the implementation of the AF scheme, the average BER for these terminals improved as shown in Fig. 8. Some amount of performance improvement was recorded for the first 4 terminals but not much, however, noticeable improvement is recorded for the rest (0.8916 to 0.6048). The percentage improvement in BER level is shown in Fig. 9. In this figure, the most optimized NB-IoT are the ones farthest from the transceiver, these 5 terminals improved by 9.5% to 17% as the overall link improvement.

6.2. *Signal quality through signal to interference plus noise ratio (SINR)*

The quality of the signals is examined through the SINR values which is the ratio of the signal power to the summation of interference power and noise power. To achieve this, the SINR values for individual NB-IoT are recorded and presented in Fig. 10.

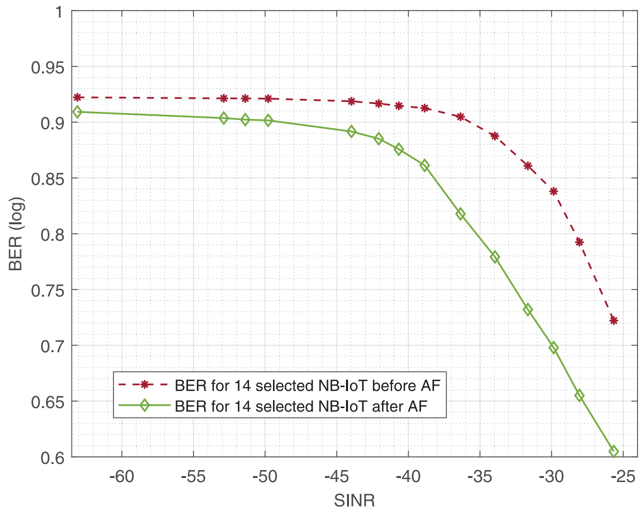

Fig. 8. The BER for 14 selected NB-IoT terminals. These terminals were identified to have higher BER before the implementation of the AF scheme, however, the BER was reduced after the implementation of the scheme with little fluctuations in the SINR values.

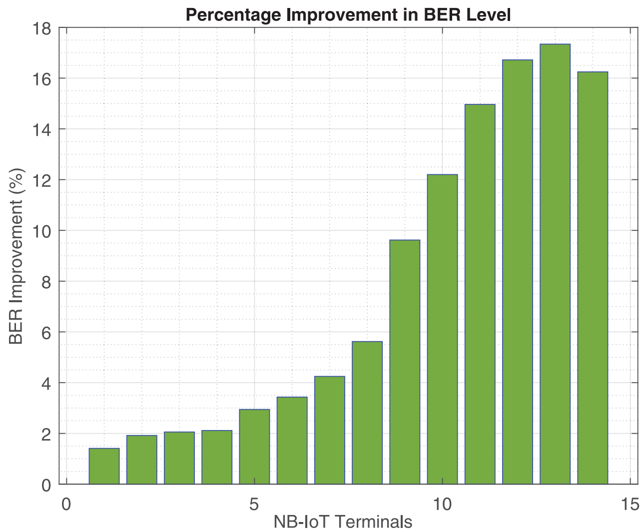

Fig. 9. Improvement in the BER level for the 14 individual terminals after the implementation of the optimization scheme.

The SINR values are in three folds; first the SINR values for the direct channel or link between an individual terminal and the transceiver, second, the SINR values for the channel between the terminal and the NAT and third, the SINR values between the NAT and the transceiver. As shown, the SINR between the NAT and transceiver has the best SINR. This is because, for the implementation of the AF scheme, a NAT with a high Signal-to-Noise Ratio (SNR) for end-to-end communication with the transceiver is chosen as explained in Section 5.2. From Fig. 10, the first four terminals have the lowest SINR values which correspond to terminals 25, 24, 23, and 22. This also translates to high BER as presented in Section 6.1.

6.3. Cumulative distribution function (CDF) and effective throughput

In this subsection, the evaluation of the system performance is presented with the aid of a Monte Carlo simulation technique to understand the effective throughput with respect to CDF. Using this simulation technique, a random sample simulation of 500 runs was conducted to analyze the effective throughput of the 14 affected NB-IoT terminals. The result is presented in two graphs, each graph represents a group of 7 terminals. To simulate this, the settings in Table 1 were used.

The CDF shows the effective throughput performance of the terminals at random values. This is a probability function that describes the distribution of the throughput data. However, the average effective throughput is the actual amount of information

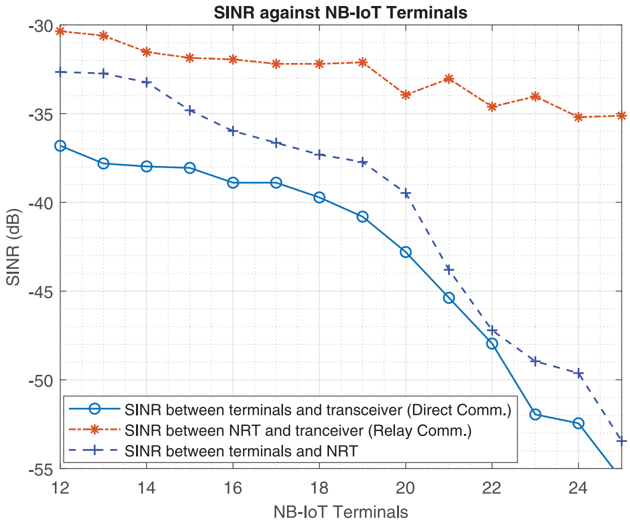

Fig. 10. The SINR value for individual NB-IoT terminals is used to determine their signal quality. The channel quality for the communication between the NRT and transceiver appeared to have the highest signal quality. While the signal quality for the direct communication between the individual NB-IoT terminals and the transceiver is lower as compared to the communication between the terminals and the NRT.

that is successfully transmitted per second over the wireless channel with all the overhead control data and it is affected by other factors such as packet loss, and interference. The first group of terminals affected (12–18) is shown in Fig. 11, the average effective throughput that is achievable is less than 90 kbps at 50% probability. The less achievable effective throughput is NB-IoT18 with 50.2 kbps. The maximum effective throughput achievable is NB-IoT12 with 152.401 kbps. Similarly, the second group of terminals affected in this scenario is shown in Fig. 12. At 50% probability, the achievable throughput is between 15.5 kbps and 60 kbps. The maximum throughput is 99.615 kbps achievable by NB-IoT25. Based on [30], this implies that the effective throughput of these terminals is lower than the uplink and downlink peak data rates of 226.7 kbps and 250 kbps respectively.

Due to the control overhead data that makes effective throughput much lower than theoretical maximum throughput, the other major factors responsible for this performance are:

- **Transmission Distance.** The distance between the base station and the NB-IoT terminals, in part, determines the strength of the signal and the amount of possible packet loss.
- **The Wireless Channel Quality.** The major contributors to this factor in industrial settings are the composition of the environment in terms of structures, material type, and obstructions along the paths of wireless transmission, as well as the type and sensitivity of transmission antenna.
- **Level of Interference from other Wireless Networks or Devices.** Other wireless devices and networks that operate within the same frequency band contribute to the reduction in the effective throughput.

7. Challenges and future research directions

The realization of a DT involves the use of several tools or software for modeling and simulations. The interoperability of these tools is not seamless and this poses a challenge. This challenge was experienced in the scenario presented in this paper. Moreover, in a real-world context, various environmental factors, such as irregular levels of noise generated, interference from other wireless networks, including field and power interference [31,32], extreme temperature [33,34], and vibrations [35] can adversely affect the specific communication channel under investigation. Incorporating these factors into the DT presented challenges, leading to the use of assumed values. Furthermore, there is a requisite for a path loss model that comprehensively characterizes wireless signal propagation within an industrial indoor setting, as expounded upon by the author in Ref. [36]. Therefore, the availability of DT tools that provide seamless and easy usage would be a step toward the advancement of DTs. These tools, such as wireless Insite, are expected to offer the capability to incorporate alternative propagation models not explicitly enumerated within the tool's predefined options. Moreover, within the context of this research, the incorporation of alternative optimization methodologies beyond the utilization of AF presents a considerable challenge. Consequently, there arises a compelling imperative for DT tools to facilitate the integration of diverse optimization techniques, thereby enhancing the attainment of more favorable results. The implication is that DTs will be adopted more rapidly and confidence in their usage will increase. To build confidence in the usage of DTs, it is necessary to focus on the accuracy of the technologies upon which DT depends, technologies such as simulation tools, AI, and ML. In the aspect of ML, there is an opportunity to enhance the scope and effectiveness of this study by integrating ML methodologies aimed at improving some of the challenges listed above in NB-IoT wireless communication in an industrial indoor environment. To leverage ML in this specific context, the following elaboration outlines the potential improvements:

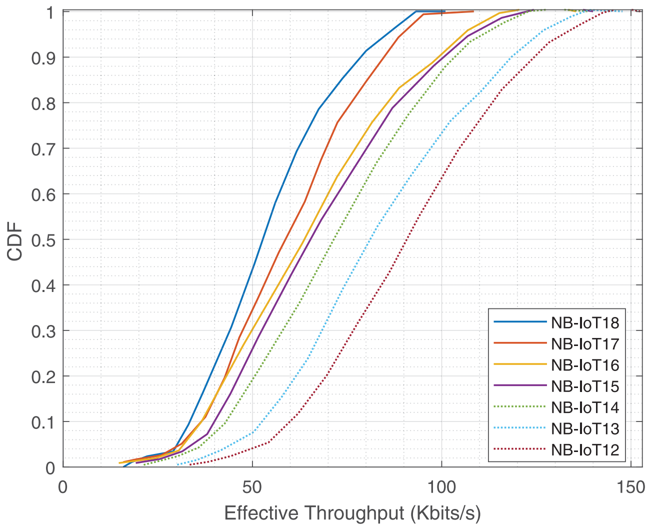

Fig. 11. The average effective throughput for the first group of the affected NB-IoT terminals (12–18) showing their cumulative distribution function (CDF).

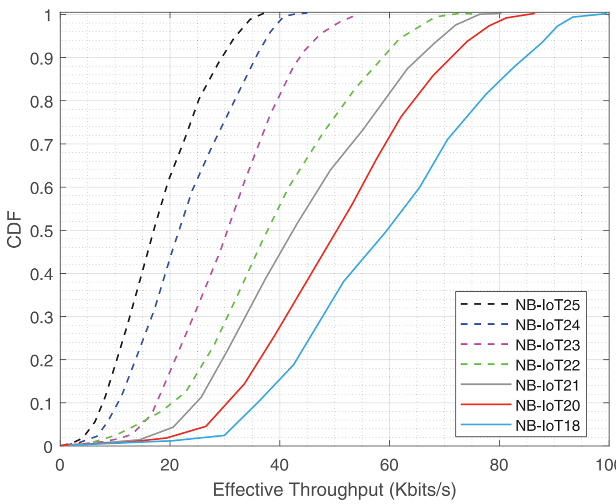

Fig. 12. The average effective throughput for the second group of the affected NB-IoT terminals (19–25) showing their cumulative distribution function (CDF).

- ML and Wireless Prediction: The use of ML techniques to predict the wireless communication of NB-IoT terminals in an industrial indoor environment while focusing on the communication parameters and set of environmental conditions gathered in the study. This should be aimed at providing a mechanism that would allow for the extrapolation of the study to other industrial facilities that share some common features.
- ML and Link Adaptation Mechanism: According to some researchers, a hybrid link adaptation strategy can be used to study how coverage enhancement features affect network reliability and latency. In this strategy, latency and coverage have been optimized. In order to achieve this, they formulated and solved an optimization problem in which the optimal value of repetitions, bandwidth, and modulation and coding scheme (MCS) is found so that latency is minimized and reliability is maintained [37]. It would, therefore, be necessary to apply ML in the link adaptation selection process for better optimization since the hybrid link adaptation method achieves lower latency and higher coverage than any other coverage enhancement technique.

8. Conclusion

This paper introduces an investigation into wireless NB-IoT optimization, focusing on the viewpoint of DT. Within this contextual framework, a technique pertaining to AF optimization is employed within the extant system model to enhance the wireless communication performance of NB-IoT. The pivotal role of DT in the progression of Industry 4.0 is expounded, accentuating the meticulous selection criteria applied to DTs and their consequential reliability. This, in turn, instills a sense of assurance within industrial management regarding the possible integration of DT within the NB-IoT and wireless communication domain in general.

The outcome of the optimization procedure is systematically examined, encompassing a comprehensive analysis of the BER both before and post-optimization. Manifest enhancements in BER are meticulously delineated for each terminal, with the most significant advancement of over 17% being observed in terminal 25. Complementing this analysis, the CDF is harnessed to elucidate the intricate nuances of the effective throughput behavior exhibited by the system. Based on the CDF, it is evident that the throughput performance of these terminals is below the uplink and downlink peak data rates as prescribed in [30]. Three major factors contribute to this behavior: transmission distance, wireless channel quality resulting from industrial structures and obstructions, and interference from other wireless networks. This is an indication of room for further optimization. Furthermore, an exhaustive inquiry into signal quality across various channels interconnecting the NAT entities, transceiver, and NB-IoT terminals is conducted, thereby providing a multifaceted perspective on the overarching communication dynamics. The communication dynamics observed in this study highlighted the channel quality between individual terminals and the NB-IoT transceiver, as well as between NAT and the transceiver. Additionally, the interactions involving poor-performing terminals communicating through the NAT were examined. Specifically, the communication link involving the transmission from poor-performing NB-IoT terminals to the NB-IoT transceiver via the NAT illustrated the practical implementation of the AF optimization scheme.

CRediT authorship contribution statement

Muhammad Dangana: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Sajjad Hussain:** Writing – review & editing, Supervision, Resources. **Shuja Ansari:** Writing – review & editing, Investigation, Formal analysis. **Muhammad Imran:** Writing – review & editing, Supervision, Resources, Project administration. **Ahmed Zoha:** Data curation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgment

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