IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 3, 2022, accepted February 17, 2022, date of publication February 22, 2022, date of current version March 3, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3153726

TTGN: Two-Tier Geographical Networking for Industrial Internet of Things With Edge-Based Cognitive Computing

SANG-HOON LEE[1], (Graduate Student Member, IEEE), TAEHUN YANG[2], (Graduate Student Member, IEEE), TAE-SUNG KIM[1], (Member, IEEE), AND SOOCHANG PARK[3], (Member, IEEE)

[1]Department of Management Information Systems, Chungbuk National University, Cheongju 28644, Republic of Korea
[2]Department of Computer Engineering, Chungnam National University, Daejeon 34134, Republic of Korea
[3]Department of Computer Engineering, Chungbuk National University, Cheongju 28644, Republic of Korea

Corresponding author: Tae-Sung Kim (kimts@chungbuk.ac.kr)

ABSTRACT Industrial Internet of Things (IIoT) is based on data acquisition and data analytics technologies. A variety of and a large amount of data is collected at management nodes with computing and storage capacities. Recently, the computing ability, denoted by the edge, has been located closer to the service fields to achieve faster and more reliable data-driven service provisioning. Edge computing is a useful resource to facilitate smart manufacturing based on IIoT. Since the current Industrial Wireless Sensor Networks (IWSNs) technologies for IIoT do not perfectly cover all the demands of industries with smart manufacturing such as agile flexibility with asset movement. A major future demand for IWSNs should be to support the mobility of assets in a wireless environment. This paper investigates the shortages of current technologies such as WirelessHART and proposes a novel wireless networking scheme based on edge-based cognitive computing in order to support reliable and low latency communication of mobile assets, which is involved in the smart manufacturing processes. We devise a two-tier geographical networking (TTGN) system that supports position-based mobility detection and networking. Also, resource allocation for the reliable and real-time has been obtained based on the game theory. Evaluation results demonstrate that TTGN can guarantee a high data transmission success ratio, as well as a fast delivery ratio for link path establishment.

INDEX TERMS Edge computing, Industrial Internet of Things, mobility, resource allocation.

I. INTRODUCTION

Recent advances in computing and wireless communication technologies are leading to the evolution of factory automation and smart manufacturing, named Industry 4.0 [1]. With the novel version of industrial technologies, companies, and manufacturers could accommodate newly-driven goals faced with constant and increased supplies of various products and growing demands for services [2]. To accommodate the increasing demand for agility, flexibility, low cost, and data-driven reconfigurable production and manufacturing in the smart factory should be developed with intelligent and low-cost automation of industrial processes [3].

In the context of intelligent manufacturing, IWSNs bring an array of advantages over wired systems in terms of elimination of the need for complex, expensive, and difficult installation of wired systems in placing production robots and manufacturing machines with sensors, reliable and real-time data gathering, and machine controls, etc [4]. The self-configuring and self-organizing capabilities of IWSNs make it an ideal choice to ensure modular structured smart factories with cyber-physical systems for decentralized and real-time decisions both internally and across organizational services for participants of the value chain [5]. Furthermore, IWSNs create a highly reliable system that rapidly responds to real-time events.

A large amount of data is generated from IIoT devices installed over IWSNs and the collected data bring information about the operations of factory [6]. The collected data from IIoT needs to be relayed, scheduled, and stored in real-time manner [7]. In addition, IIoT in the manufacturing system requires attributes such as location awareness and low latency [8]. The advanced factories deployed IIoT can also self-configure the equipment and material flows depending

The associate editor coordinating the review of this manuscript and approving it for publication was Marco Martalo.

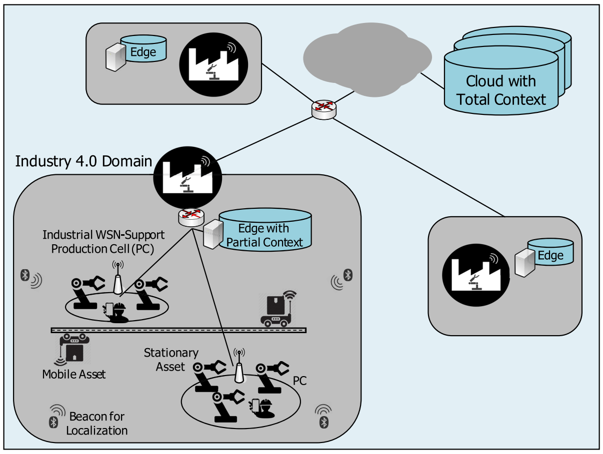

FIGURE 1. Industrial IoT system architecture for industry 4.0.

on the product being built and schedule changes, and then see the impact of those changes in real-time [9]. The smart factories that Industry 4.0 fosters should rely on the reconfigurable manufacturing unit, reconfigurable production line, and intelligent data acquisition which enable the application of business logic between the downstream data of the cloud service and the upstream data of the IIoT configured with IWSNs [10]. In other words, in the Industry 4.0 domain, there are multiple production cells (PCs) supported by IWSNs. Each PC includes a wide variety of industrial assets such as producing robots, autonomous mobile robots, various vehicles, sensing devices, workers with handheld devices, and so on [11].

Nowadays, WirelessHART [12] is emerging as a standard solution for IWSNs, providing a simple, reliable, and secure communication protocol [13]. WirelessHART is one of the first standards of a wireless sensor networking technology developed for industrial process automation and based on the Highway Addressable Remote Transducer (HART) Protocol [14]. Also, WirelessHART is a global IEC-approved standard (IEC 62591) that specifies an interoperable self-organizing mesh technology. Industry field devices and instruments form wireless networks that dynamically mitigate obstacles in the process environment with WirelessHART [15]. IWSNs based on the WirelessHART can communicate data back to host systems securely and reliably, and can be used for both control and monitoring applications [16]. Furthermore, WirelessHART is backward compatible with HART, which can send and receive digital information over analogue wires between control and monitoring systems.

The smart factory needs to be highly scalable, reliable, and real-time systems [17]. In addition, a self-organization dynamic scheduling with agility is very important [18]. Agile flexibility allows advanced factories to adapt the schedule and product changes with minimal intervention. Agility can increase factory uptime and yield by minimizing changeovers due to scheduling or product changes for flexible scheduling.

However, the current IWSNs technologies such as WirelessHART have the inherent restriction with respect to the mobility support of assets since they have been initially designed to take over the same missions from reliable and secure wired technology like HART and to take advantage of wireless networks [16]. A major future demand for industrial wireless systems could be the capability to support the mobility [19]. Thus, this paper explores the way to support mobility of assets in the smart factory environments.

There are multiple production cells, and each production cell includes various industrial assets shown in Figure 1. Edge computing aims to support the operation, maintenance, scalability, and reliability of the data by creating a framework with the capability of integrating core capabilities such as networking, computing storage, and application. Also, all the edges are managed by a cloud platform to cover the networking of a smart factory.

In this paper, a mobility support scheme is proposed in the Industry 4.0 domains as shown in Figure 1. The proposed mobility support scheme has goals to achieve reliable and low latency communication for data acquisition and control transport. The proposed scheme is built on WirelesHART and relies on the edge computing paradigm to facilitate faster cognitive computing and offloading from the cloud to cover the whole domains in a smart factory. The main contributions of the proposed mobility support scheme in this paper are as follows:

- it provides a fine-grained mobility detection and resource management mechanism relying on a deep neural network-based localization technique;
- the long-term movement prediction is addressed to support successive mobility support of an asset with long-term resource allocation based on game theory;
- fast link path construction based on resource allocation and management mechanisms is presented to tune up the current WirelessHART protocol.

The rest of this paper is organized as follows. In section II, we present the state-of-the-art in terms of the smart factory, edge computing, cognitive computing, and localization technologies. In section III, the proposed mobility support scheme is addressed in detail. Then, the various experimental results are explained in section IV. Finally, we conclude this paper with performance evaluation results.

II. STATE-OF-THE-ART

In this section, the recent studies are analyzed to find out shortages of the current works related to the smart manufacturing and factory automation with novel computing and communication technologies.

A. WSN AND IoT FOR INDUSTRIES

To alleviate limitations of the traditional wired system like HART, wireless networking technologies such as IEEE 802.15.4 [20], ISA 100.11A [21], and WirelessHART are exploited in the industrial system denoted by IWSNs. The wireless networks promise lower installation costs rather than wired systems since each wireless sensor could install easily on industrial assets and instruments [22]. While the wired network leads to more complex wiring, the wireless networks are easy to set up simply because it has self-organization ability. Particularly, they facilitate the addition, removal, and relocation of industry devices such as lathe, milling, production robots, and so on for newly-demanded low-volume, high-variety production.

Discussion on IWSNs techniques to find favourable technologies and standards for industrial applications is a highly complicated subject since they share the same physical layer specifications (IEEE 802.15.4 2.4GHz DSSS radio) and only bear the slightest resemblance in the higher layers. However, ISA 100.11A cannot support backward compatibility with the widely used HART network in the industrial process. Thus, WirelessHART is a suitable wireless solution for satisfying the various industrial requirements such as real-time, reliability and security, and support backward compatibility with native HART network for reducing the installation costs [13]. This paper focuses on WirelessHART standard as the main wireless solution for industrial processes.

WirelessHART has been standardized to fill the existing gap in the industrial wireless communication standardization. It is an extension of the widely used HART communication protocol. It is designed to be not only simple-to-use, self-organizing, self-healing, and flexible, but also reliable and secure. Also, WirelessHART network is a centrally managed mesh network [23]. It is built upon IEEE 802.15.4 physical layer with datalink, network and application layer. Industrial security and authentication are reached through 128-bit AES algorithms that cover end-to-end and hop-to-hop communications. Media access control (MAC) is based on time division multiple access (TDMA) scheduled with frequency hopping. Reliability is achieved using methods of frequency diversity, path diversity, and message delivery retrials. Energy consumption could be efficiently optimized by proper management of the communications schedule. Security, reliability, scalability, low energy consumption, and backward compatibility are fundamental in WirelessHART. However, the current WirelessHART easily suffers from asset mobility in terms of such reliable and real-time properties.

B. EDGE FOR COGNITIVE COMPUTING

Edge computing extends the capabilities of computation, network connection, and storage from the cloud to the edge of the network [8]. The development of smart applications based on edge computing is continuously expanding more and more toward our living places, manufacturing domains, and even transportations areas. The next generation intelligent manufacturing, so-called smart factory, is composed of a variety of device components such as autonomous mobile robots (AMRs) transporting factory assets through logistics, robotic production lines with programmable logic controllers (PLCs), cranes and trucks embedded with various sensors, and so on [5]. There are static and mobile components in the domain, and they dynamically form manufacturing cells in order to achieve responsive operation and flexible production. Also, sensing data should be acquired at some places and computed for extracting information. In the smart factory, edge computing provides added benefits of not only increasing agility, real-time processing, and autonomy to create value for intelligent manufacturing but also decreasing overhead for centralized management of the cloud platform.

Recently, mobile edge computing has been considered as the adequate place in even 5G mobile systems for such smart applications [24]. The smart service provisioning is based on cognitive computing such that data acquisition and analytics should be fulfilled in closer places for time-constrained applications. Mobile edge computing is increasingly used in various application designs. On the other hand, cognitive computing for context-awareness, to generate information or intelligence eventually, has been facing a boosting technology in the last couple of years. Recently, the state-of-the-art researches have been worked based on deep neural network (DNN). The DNN technologies (e.g., multi-layered neural network, convolutional neural network, reinforcement learning, autoencoder, etc.) are exploited in a variety of smart applications. Thus, up-to-date studies have been worked on communication or IoT related services such as indoor localization [25], [26], user activity sensing [27], and so on.

Cognitive computing methods are based on one model: train offline-use online. It means that data acquisition is fulfilled as pre-operation separately; then, data training into designed DNN is performed at a cloud or a cloud-edge hierarchy as an offline operation. Finally, trained weight of the DNN for the real-time sensory data is used for the goal of their application.

III. TTGN: TWO-TIER GEOGRAPHICAL NETWORKING FOR INDUSTRIAL INTERNET OF THINGS

This section explains the proposed mobility support scheme above the WirelessHART protocol. The proposed scheme consists of two layers for an asset localization and mobility management layer and a link path construction and data dissemination layer. Here, such two-layered organization of the proposed scheme is called two-tier networking architecture. As shown in Figure 2, TTGN is composed of 1) edge computing tier involving DNN based localization and position-based mobility detection/resource allocation and 2) Industrial WSN tier for position/link path query and networking path establishment.

A. TTGN ARCHITECTURE

TTGN shows two-tier architecture as shown in Figure 2, and each tier is a modular subsystem according to key functionalities. In the edge computing tier, the data management module performs data acquisition from all assets in the industrial WSN area. The industrial WSN area indicates a production cell in an Industry 4.0 domain as shown Figure 1. In the Industry 4.0 domain, i.e., a smart factory domain, there are multiple production cells. Each production cell is configured for specific product manufacturing, and then it is kept until asset units in the cell need to be reconfigured for the other product in the same place or a different location in a factory

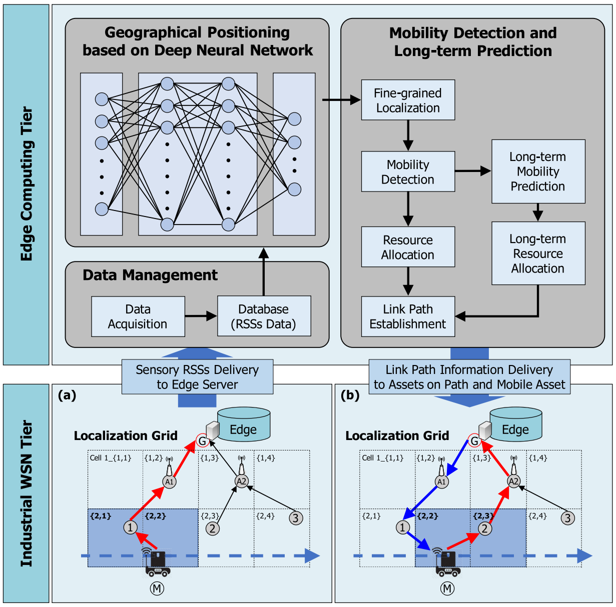

FIGURE 2. TTGN architecture over industrial WSN.

domain. Thus, the production cell (PC) can have a unique ID (e.g., PC_ID). All the assets in a PC would be dealt with by the PC_ID during the lifetime of the PC controlled by the manufacturer or manager of the smart factory. The data from all assets per PC and assets working as inter-PC missions like AMRs are collected at the data management module and the Radio Signal Strength (RSS) data of each device is used as input of the geographic positioning module.

The geographic positioning module is composed of multi-layer perceptron (MLP) based on DNN and it can predict the location of the queried asset.

Data sets are RSSs of Bluetooth Low Energy (BLE) beacons at each grid cell as shown in Industrial WSN Tier of Figure 2. All the data sets have labelled by the coordinates. When any asset uploads its current RSS value tuples, the geographic positioning module can detect where the asset is within the localization grid over a PC. After the geographic positioning module gets a result for positioning, it tosses the result to the mobility detection and long-term prediction module. The module first fulfills the resource allocation to the graph topology, and then it additionally arranges channel resources to the mobile assets. Based on the resource allocation, the module also tries to establish a link path from/to all assets including mobile devices. After receiving the resource allocation information and path information, all nodes start upstream and downstream communications.

As shown in Figure 2(a), the mobile node N_M is currently attached to sensor node 1, then it uploads its detected RSS tuples to the edge. The edge could detect where the mobile node N_M exists so that it allocates channel resources to access point 1 (A1), sensor node 1, and the mobile node N_M. Since the mobile node N_M keeps moving along with the blue arrow and it still reports its RSS data, the edge figures out that it will be attached to sensor node 2 and will exploit the link path node 2-A2-G (gateway). Thus, the edge provides this information to the mobile node N_M by the current link path, i.e., the blue path in Figure 2(b), and then the mobile node N_M will connect to the sensor node 2. The mobile node N_M can communicate after being connected to the sensor node 2, because the channel resources of all sensor nodes on the new path (red arrows) have already been allocated.

B. MLP FOR ASSET MOBILITY DETECTION AND PREDICTION

For the mobility detection and long-term prediction in the edge computing tier, the fine-grained localization based on the positioning result is fulfilled. The module can update the current position map of all assets upon the localization grid and then classifies whether the asset is a mobile or stationary device. If the asset is mobile device, the mobility management phase considers a wireless networking graph topology to update and predict the mobility of the mobile device.

The MLP should be pre-trained by a large amount of data to accommodate the required position prediction accuracy. In the MLP, each node can be performed by two functions: summation and activation. The product of inputs, weights, and bias are computed using the function by Equation 1.

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

where n, x_i, β_j, and w_{ij} show the number of inputs, the input variable of i, bias term, and the connection weight, respectively. Sigmoid function is used for an activation function in the MLP model. Sigmoid function is described in Equation 2, and the output of the neuron j can be obtained by Equation 3 as follows:

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

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

C. ASSET MOBILITY SUPPORT

This subsection presents the mobility support mechanism in detail. The edge acquires data from all assets, and it manages networking, positioning, and security. That is, the edge could be the network, position, and security manager. In WirelessHART, there is the network and security manager to configure the network graph topology for uplinks and downlinks. Thus, TTGN tunes up this manager as the advanced network manager with mobility support ideas and the positioning manager with geographic positioning module and the mobility detection and long-term prediction module.

After the mobile node N_M uploads its RSS data tuples to the edge a couple of times, the edge can figure out the moving direction and speed of the mobile node N_M. It means that the edge can determine the grid cells for the mobile node N_M. Then, the edge makes schedules to allocate channel resources upon the link paths to be established for the mobile node N_M. TTGN deals with such mobility management in the long-term mobility prediction and the long-term resource allocation

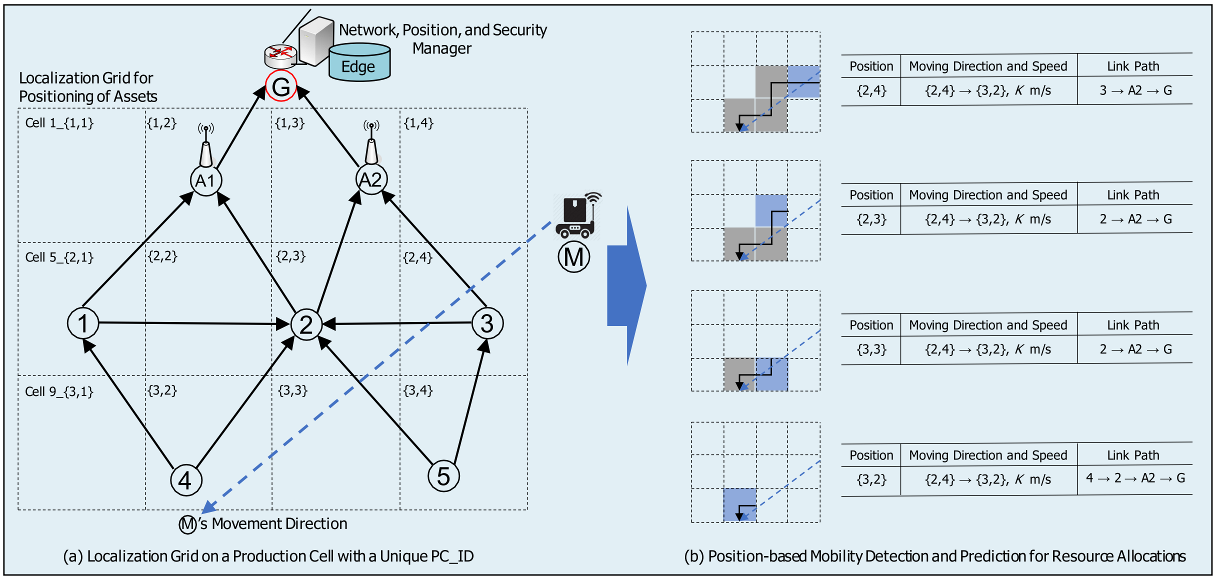

FIGURE 3. **Mobility detection and long-term prediction based on edge-based network cognition.**

in the mobility detection and long-term prediction module. After the mobile node N_M receives the long-term mobility support information from the edge, it won't upload its RSS data to the edge. However, if the mobile node N_M detects changes related to moving direction and speed of itself, it will report its RSS data again quickly. After that, the edge tries to detect the new direction and speed to manage the mobile node N_M.

Figure 3 illustrates the long-term mobility detection and the predictive establishment of link paths along with the moving direction and speed of the mobile node. Edge which is connected to the access points (i.e., A1 and A2) acquires data from all assets through the access points (APs). Also, all the assets can transmit their data and relay information from other assets utilizing WirelessHART supporting mesh network.

After the mobile node N_M reports its RSS data tuples to the edge several times, the edge can figure out the moving direction of the mobile node N_M and determine N_M's moving speed. Thus, the edge also knows that the mobile node N_M will passes by the cell {2,4}, {2,3}, {3,3}, and {3,2} in consecutive order. If the direction and speed are not changed, the link paths are constructed successively. Figure 3(b) shows the path information changes along with N_M's movement.

D. RESOURCE ALLOCATION BASED ON GAME THEORY

We develop a game-theoretic approach to achieve reliable and low latency communication for data acquisition in the smart manufacturing process. Game theory is a theoretical framework in which competitors make strategic decisions based on expectations or predictions of their opponents in an interdependent situation [28].

In Figure 4, the mobile node N_M passes through the cell {2,4}, {2,3} and {3,2} with the blue arrow, where N_M selects a sensor node N_i at each cell. There are two or three sensor

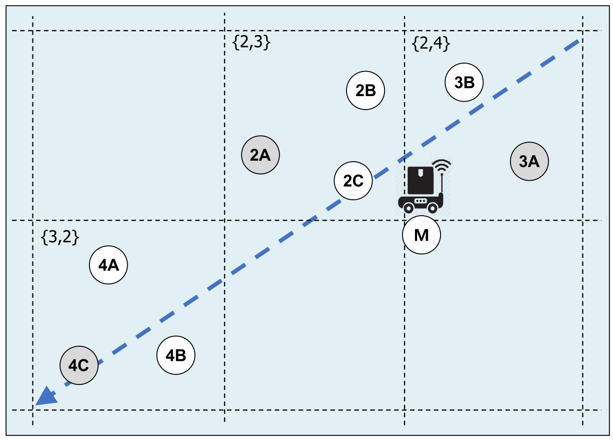

FIGURE 4. **Resource allocation based on game theory.**

node in each cell. N_M selects 3A in the cell {2,4}, 2A in the cell {2,3} and 4C in the cell {3,2}. The best response strategy [29] is used to consider the strategy of each sensor node N_i in a cell. Then, the edge calculates the Nash equilibrium of all the cells for resource allocation.

The game model is composed of players, strategies and payoff [28]. N_i is a sensor node of player i, where $i = \{1, 2, \ldots, n\}$. The terms player and the sensor node N_i are used interchangeably, because the sensor nodes are players in the game model. In addition, N_{-i} represents all players except player N_i. S_i is a strategy of player i and can be represented as $S_i = \{0, 1\}$. $S_i = 0$ means that S_i is not connected with the mobile node N_M, whereas $S_i = 1$ indicates that S_i is connected with the mobile node N_M. For the resource allocation, we define a payoff of the strategy of player i as $P_i = [d_i, l_i]$. Payoff P_i consists of values d_i which is the distance between the sensor node N_i and the mobile node N_M, and the data loss ratio l_i from sensor node N_i to the edge. The important notations for the game theory model are summarized in Table 1.

TABLE 1. Summary of notations.

Notation	Description
N_M	Mobile node
N_i	Sensor node of player i
N_{-i}	All players except player i
S_i	Strategy of player i
P_i	Payoff of the strategy of player i
d_i	Distance between N_i and N_M
l_i	Data loss ratio from N_i to edge

To derive a Nash equilibrium as a solution of the game, the best response strategy is used. For any given actions of the players other than player i, player i's action makes various payoffs for its strategies. We are interested in the best strategy, which has the highest payoff among various payoffs. The strategy $S^* = (S_i^*, S_{-i}^*)$ is a best response strategy if $P_i(S_i^*, S_{-i}^*) \geq P_i(S_i, S_{-i})$ for each player i. If the set of strategy is a Nash equilibrium of the game, no player change their strategy. A Nash equilibrium is an action of strategy profile that is not changed because every player's strategy is a best response to the other players' strategy. Resource allocation decision profile $S^* = (S_1^*, S_2^*, \ldots, S_n^*)$ is a Nash equilibrium if any node cannot further increase its benefit by changing its strategy. A Nash equilibrium S_i^* of player i can be defined as follows:

$$P_i(S_i^*, S_{-i}) \geq P_i(S_i, S_{-i}). \tag{4}$$

The best response strategy and the Nash equilibrium can be applied to update the resource allocation. According to the vector of the mobile node N_M, the edge calculates the best response strategy of sensor node N_i. After calculating the best response strategy of each sensor node N_i in the same cell, the edge derive the Nash equilibrium NE_i, where $i = \{1, 2, \ldots, n\}$. Nash equilibrium includes the best response strategy of all the sensor nodes. To consider the long-term resource allocation, we consider all the production cells in the smart factory. The long-term resource allocation can be represented as the set of the Nash equilibrium $NE = \{NE_1, NE_2, \ldots, NE_n\}$.

Algorithm 1 shows a procedure of resource allocation. The edge detects a mobility for each mobile node N_M. The mobility consists of a location of each N_M and a moving speed. The edge could predict a series of cells $List_{cell}$ on the movement path of N_M through the tracking with consecutive mobility awareness. Then, the edge selects one of sensor nodes N in each cell $Cell_c$ of $List_{cell}$. To select one sensor node, the edge calculates the best response strategy S with the payoff P for every sensor node. The result of S and information of N are inserted into a set of strategies S_{set}. Then, the sensor node is selected by NE with S_{set} in each cell. This procedure is repeated until the end of processing for every $Cell$. As a result of the procedure, NE_{set} includes a list of sensor nodes, which are able to communicate with N_M, for each cell. Eventually, the edge performs the resource allocation as NE_{set}. In other words, the edge with Algorithm 1 conducts not only the resource allocation for one cell but also the long-term resource allocation for a series of cells.

Algorithm 1 Resource Allocation Algorithm

$List_{cell} = PredictionCellEntries(N_M)$
for $Cell_c$ in $List_{cell}$ **do**
  for N_i in $Cell_c$ **do**
    $P = [getDist(N_i), getLoss(N_i)]$ // Payoff
    $S = calculateBestRespStrategy(P)$ // Strategy
    $S_{set}.insert(N_i, S)$
  end for
  $NE_c = NashEquilibrium\_Cell(S_{set})$
  $NE_{set}.insert(NE_c)$
end for
for NE_i in NE_{set} **do**
  $ResourceAllocation(NE_i)$
end for

IV. PERFORMANCE ANALYSIS

A. PROOF-OF-CONCEPT AND TESTBED SETUP

In this section, we evaluate the performance of the proposed scheme. Proof-of-concept consists of an edge, APs, the stationary node with a beacon signal, and a smartphone. Performance analysis is divided into MLP performance results and resource allocation optimization and TTGN results. The number of nodes for localization and resource allocation is set to 4 (3 stationary nodes and 1 moving smartphone) and 9 (8 stationary nodes and 1 moving smartphone), respectively. Experimental environments are listed in Table 2.

B. MLP PERFORMANCE FOR LOCALIZATION RESULTS

MLP on the edge predicts a geographical position of a smartphone. For this experiment, MLP trains 800 RSSs for localization of a moving smartphone with 3 stationary nodes with a beacon signal. Then, MLP tests the position of a smartphone with 400 RSSs. We measure the training time, the prediction time and the prediction accuracy for MLP. Then we evaluate performance for MLP. The number of nodes in the output layer is the same as the number of cells to be predicted. Besides, in each hidden layer, the number of hidden nodes is set to 10 or 20 according to experimental environments.

Figure 5 shows a MLP performance implemented on the edge. MLP performance is affected by various factors such as the number of layers and the number of nodes per layer. MLP10 and MLP20 mean the number of hidden nodes. Those represent 10 and 20 hidden nodes, respectively. The number of hidden nodes has an impact on prediction accuracy as well as the training time and the prediction time. The prediction accuracy increases in proportion to the number of hidden nodes, and the training time and prediction time also increase. The prediction accuracy in MLP10 has about 96 percent, in MLP20 has about 100 percent. In Figure 5(a), the training time in MLP10 has about $2s$, in MLP20 has about $4.6s$. In Figure 5(b), the prediction time in MLP10 has about $1ms$, in MLP20 has about $3ms$. This phenomenon may require a large of resources on the edge server for localization and mobility support on the network. However, the training time and the prediction time are very short. In addition, the training

TABLE 2. Proof-of-Concept and experiment setup.

Feature Name	Experimental Environments
Mobile OS	Android version 6.0 (API Level 23)
# of Nodes	4∼9 (3∼8 Stationary nodes and 1 Moving Smartphone)
Moving Speed	About 1m/s
Edge Server	Linux OS With Django 2.1.3
MLP Implementation	Python 3.6.6, TensorFlow 1.11.0
MLP Epoch	200
MLP # of Layers	4 (Including Input/Output Layers)
MLP # of Nodes	10, 20 (Per Hidden Layers)
MLP # of Training Data	800
MLP # of Test Data	400

frequency is low since the training is performed only when a certain amount of data is collected. And the prediction is periodically performed to predict the geographical positions of all the nodes on the network, but the required time for the prediction is $1ms$ to $3ms$, which does not have a large effect on the edge server. This experiment shows that MLP for localization is sufficiently applicable to the edge server.

C. RESOURCE ALLOCATION OPTIMIZATION AND TTGN RESULTS

Figure 6 shows optimization results based on the game theory. To derive the best response strategy and the Nash equilibrium, we used the payoff of each sensor node and measured the signal strength of the APs for the communication between APs and the mobile node. The signal strength range is measured from −87dBm to −73dBm. We set up the environment for the resource allocation experiment, like Figure 4 with 8 stationary nodes with a beacon signal in 3 cells.

Figure 6(a) shows the cumulative loss ratio on each cell. In the non-optimization model, as the number of cells increases, data loss increases. Also, the graph of game theory optimization shows the increase in loss ratio as cells increase. This is because we have not considered any constraints for the optimization model. However, comparing the graphs in Figure 6(a), the game theory optimized one is lower than the non-optimized one. In this result, it can be assumed that data loss decreases in the optimized model as the number of cells increases.

In Figure 6(b), the game theory based optimization approach shows the stable transmission success ratio at each iteration. The best response strategy of each sensor node means the best value of the payoff for each sensor node. Thus, the set of the best response strategy (i.e., Nash equilibrium) is to maximize the payoff of all nodes in each cell. However, the non-optimization resource allocation is unstable in comparison with the game theory optimized graph at each iteration. This is because the non-optimization model calculated in the edge allocates the sensor node randomly. Therefore, the values of non-optimization are lower or the same as the values of the game theory optimization model.

Figure 7 indicates the comparison of proposed TTGN and original WirelessHART about mobility support.

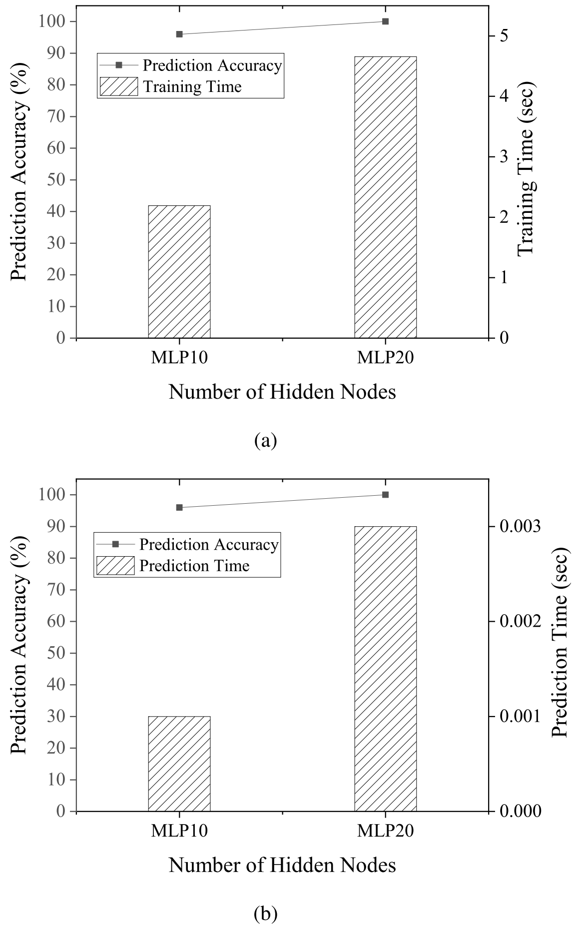

FIGURE 5. MLP performance for position prediction accuracy and time duration.

As a comparison target, we choose Han Routing scheme [16], which is widely used in original WirelessHART. Figure 7(a) shows the packet delivery success ratio for TTGN and Han Routing scheme. The Han Routing scheme has 84% of success ratio, and the proposed scheme has 98% of success ratio. All of the industrial assets periodically report a health report message to the network manager through their industrial wireless sensor network. A link path failure by the mobility of assets makes it impossible to send the message to the network manager. That is, the mobility has an impact on the packet delivery success ratio. To prevent packet loss by a link path failure, the mobility detection of assets is important. The Han Routing scheme takes a relatively long time to recover the link path compared to the proposed scheme. Therefore, the number of packets lost during the link path failure period is larger than the proposed scheme. On the other hand, in the proposed scheme, a few packets are lost since the proposed scheme supports network-based mobility detection in the edge server. The long-term mobility prediction function in the edge server predicts the moving direction and speed of mobile assets, and then the long-term resource allocation function allocates a resource for the mobile asset to every asset on a moving path. That is, although the mobile asset continuously moves, the mobile asset can immediately transmit packets

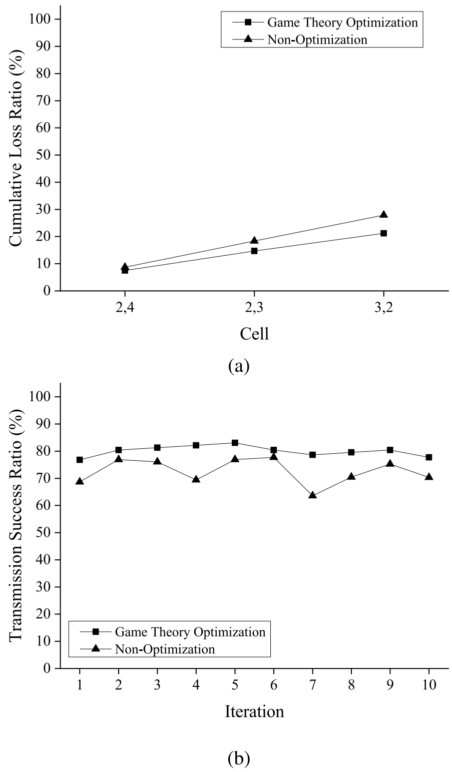

FIGURE 6. Resource allocation performance for optimization.

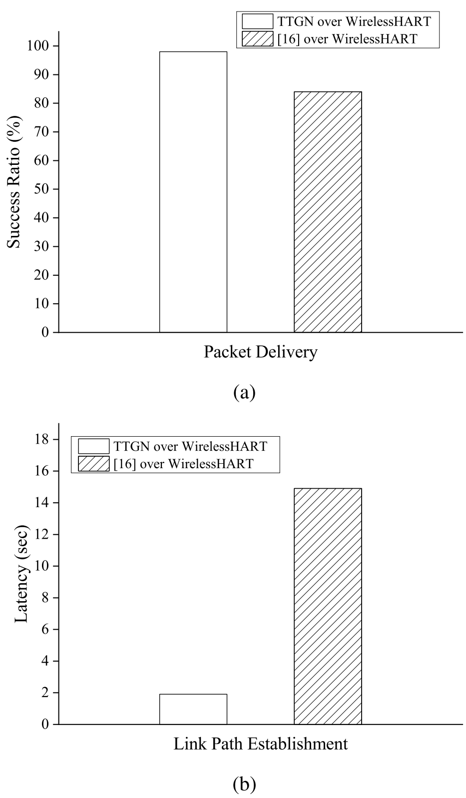

FIGURE 7. Mobility support impacts on success ratio and latency.

to the nearby asset locally. Thus, the proposed scheme has a higher packet delivery success ratio than the Han Routing scheme.

Figure 7(b) presents the latency for link path establishments. This means the time required to establish a new link path as the network topology changes by asset movement. The proposed and Han Routing schemes require around $15s$ and $2s$, respectively. Link path establishment is closely related to mobility detection of assets. Since the Han Routing scheme does not support mobility detection, the network manager recognizes the change of the network topology after a mobile asset is disconnected from the network. The mobile asset discovers a neighbour asset that can be connected to the network and be able to request resource allocation to the network manager. The Han Routing scheme is inefficient since it takes considerable time. On the other hand, the proposed scheme supports mobility detection in the edge server. When an asset moves, the edge server predicts a moving path based on a geographical position of an asset and then allocates radio resources. Then, the edge server delivers new link path information to both the closest asset geographically on the moving path and the mobile asset. Since this process is performed before the mobile asset is disconnected, it is possible to minimize the link path recovery time for the link path failure. Thus, the proposed scheme consumes very shorter time than the Han Routing scheme for link path establishment.

V. CONCLUSION

This paper explores shortages of the current IWSNs technologies, mainly WirelessHART. As WirelessHART performance suffers from asset mobility issues, TTGN has come up with. TTGN relies on the edge to support the mobility of the assets. The edge-based localization and short-range and long-term mobility prediction can continuously hold the reliable and real-time properties of WirelessHART, although the assets based on IWSNs are heterologous, i.e., stationary and mobile nodes. Specifically, long-term resource allocation has been obtained based on the game theory via the best response strategy and the Nash equilibrium. The performance evaluation results demonstrate that the data transmission success ratio is almost 80% and data loss is lower than the non-optimization model. In addition, the proposed TTGN scheme shows improvement in terms of packet delivery ratio and is 7.5 times faster than the original WirelessHART for link path establishment. In future work, multiple mobile nodes and stationary nodes in production cells will be considered for supporting a lot of nodes with a realistic smart factory environment.

REFERENCES

[1] D. Sinha and R. Roy, "Reviewing cyber-physical system as a part of smart factory in industry 4.0," *IEEE Eng. Manag. Rev.*, vol. 48, no. 2, pp. 103–117, Jun. 2020.

[2] K. Islam, W. Shen, and X. Wang, "Wireless sensor network reliability and security in factory automation: A survey," *IEEE Trans. Syst., Man, Cybern., C (Appl. Rev.)*, vol. 42, no. 6, pp. 1243–1256, Nov. 2012.

[3] M. Hermann, T. Pentek, and B. Otto, "Design principles for industrie 4.0 scenarios," in *Proc. 49th Hawaii Int. Conf. Syst. Sci. (HICSS)*, Jan. 2016, pp. 3928–3937.

[4] J. Wan, S. Tang, D. Li, M. Imran, C. Zhang, C. Liu, and Z. Pang, "Reconfigurable smart factory for drug packing in healthcare industry 4.0," *IEEE Trans. Ind. Informat.*, vol. 15, no. 1, pp. 507–516, Jan. 2019.

[5] M. Aazam, S. Zeadally, and K. A. Harras, "Deploying fog computing in industrial Internet of Things and industry 4.0," *IEEE Trans. Ind. Informat.*, vol. 14, no. 10, pp. 4674–4682, Oct. 2018.
[6] D. A. Chekired, L. Khoukhi, and H. T. Mouftah, "Industrial IoT data scheduling based on hierarchical fog computing: A key for enabling smart factory," *IEEE Trans. Ind. Informat.*, vol. 14, no. 10, pp. 4590–4602, Oct. 2018.
[7] P. Lade, R. Ghosh, and S. Srinivasan, "Manufacturing analytics and industrial Internet of Things," *IEEE Intell. Syst.*, vol. 32, no. 3, pp. 74–79, May/Jun. 2017.
[8] B. Chen, J. Wan, A. Celesti, D. Li, H. Abbas, and Q. Zhang, "Edge computing in IoT-based manufacturing," *IEEE Commun. Mag.*, vol. 56, no. 9, pp. 103–109, Sep. 2018.
[9] A. Karaagac, E. De Poorter, and J. Hoebeke, "In-band network telemetry in industrial wireless sensor networks," *IEEE Trans. Netw. Service Manage.*, vol. 17, no. 1, pp. 517–531, Mar. 2020.
[10] E. Sisinni, A. Saifullah, S. Han, U. Jennehag, and M. Gidlund, "Industrial Internet of Things: Challenges, opportunities, and directions," *IEEE Trans. Ind. Informat.*, vol. 14, no. 11, pp. 4724–4734, Nov. 2018.
[11] A. Orsino, A. Ometov, and G. Fodor, "Effects of heterogeneous mobility on D2D- and drone-assisted mission-critical MTC in 5G," *IEEE Commun. Mag.*, vol. 55, no. 2, pp. 79–87, Feb. 2017.
[12] *Industrial Networks—Wireless Communication Network and Communication Profiles—WirelessHART*, document IEC 62591, International Electrotechnical Commission, 2009.
[13] M. Nobre, I. Silva, and L. Guedes, "Performance evaluation of WirelessHART networks using a new network simulator 3 module," *Comput. Elect. Eng.*, vol. 41, pp. 325–341, Jan. 2015.
[14] K. Al Agha, M.-H. Bertin, T. Dang, A. Guitton, P. Minet, T. Val, and J.-B. Viollet, "Which wireless technology for industrial wireless sensor networks? The development of OCARI technology," *IEEE Trans. Ind. Electron.*, vol. 56, no. 10, pp. 4266–4278, Oct. 2009.
[15] A. Saifullah, Y. Xu, C. Lu, and Y. Chen, "Real-time scheduling for wirelessHART networks," in *Proc. 31st IEEE Real-Time Syst. Symp.*, Nov. 2010, pp. 150–159.
[16] S. Han, X. Zhu, A. K. Mok, D. Chen, and M. Nixon, "Reliable and real-time communication in industrial wireless mesh networks," in *Proc. IEEE Real-Time Embedded Technol. Appl. Symp.*, Apr. 2011, pp. 3–12.
[17] V. Modekurthy, A. Saifullah, and S. Madria, "DistributeHART: A distributed real-time scheduling system for wirelessHART networks," in *Proc. IEEE Real-Time Embedded Technol. Appl. Symp.*, Apr. 2019, pp. 216–227.
[18] J. Wan, B. Chen, S. Wang, M. Xia, D. Li, and C. Liu, "Fog computing for energy-aware load balancing and scheduling in smart factory," *IEEE Trans. Ind. Informat.*, vol. 14, no. 10, pp. 4548–4556, Oct. 2018.
[19] S. Montero, J. Gozalvez, M. Sepulcre, and G. Prieto, "Impact of mobility on the management and performance of wirelessHART industrial communications," in *Proc. IEEE 17th Int. Conf. Emerg. Technol. Factory Autom. (ETFA)*, Sep. 2012, pp. 1–4.
[20] *IEEE Standard for Information Technology Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (LR-WPANs)*, IEEE Standard 802. 15. 4, 2020. [Online]. Available: https://standards.ieee.org/ieee/802.15.4/7029/
[21] *Wireless Systems for Industrial Automation: Process Control and Related Applications*, Standard ISA-100.11a-2009, International Society of Automation, 2009.
[22] L. Zheng, "Industrial wireless sensor networks and standardizations: The trend of wireless sensor networks for process autometion," in *Proc. SICE Annu. Conf.*, Aug. 2010, pp. 1187–1190.
[23] J. Song, S. Han, A. Mok, D. Chen, M. Lucas, M. Nixon, and W. Pratt, "WirelessHART: Applying wireless technology in real-time industrial process control," in *Proc. IEEE Real-Time Embedded Technol. Appl. Symp.*, Apr. 2008, pp. 377–386.
[24] J. Jin, J. Luo, Y. Li, and R. Xiong, "COAST: A cooperative storage framework for mobile transparent computing using device-to-device data sharing," *IEEE Netw.*, vol. 32, no. 1, pp. 133–139, Jan./Feb. 2018.
[25] H. Chen, Y. Zhang, W. Li, X. Tao, and P. Zhang, "ConFi: Convolutional neural networks based indoor Wi-Fi localization using channel state information," *IEEE Access*, vol. 5, pp. 18066–18074, 2017.
[26] W. Li, Z. Chen, X. Gao, W. Liu, and J. Wang, "Multimodel framework for indoor localization under mobile edge computing environment," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4844–4853, Jun. 2019.
[27] D. Ravì, C. Wong, B. Lo, and G.-Z. Yang, "A deep learning approach to on-node sensor data analytics for mobile or wearable devices," *IEEE J. Biomed. Health Inform.*, vol. 21, no. 1, pp. 56–64, Jan. 2017.
[28] J. von Neumann and O. Morgenstern, *Theory of Games and Economic Behavior*. Princeton, NJ, USA: Princeton Univ. Press, 1953.
[29] U. Berger, "Best response dynamics for role games," *Int. J. Game Theory*, vol. 30, no. 4, pp. 527–538, May 2002.

SANG-HOON LEE (Graduate Student Member, IEEE) received the bachelor's degree in business administration and the master's degree in management information systems from Chungbuk National University, Republic of Korea, in 2016 and 2018, respectively. He is currently pursuing the Ph.D. degree. His research interests include operations research, game theory, and information security.

TAEHUN YANG (Graduate Student Member, IEEE) received the B.S. degree in computer engineering from Chungnam National University, Daejeon, South Korea, in 2014, where he is currently pursuing the Ph.D. degree in computer engineering. His research interests include mobile sensing, wireless communication, networking technologies, and the Internet of Things.

TAE-SUNG KIM (Member, IEEE) received the bachelor's, master's, and Ph.D. degrees in engineering from the Department of Management Science, KAIST, in 1991, 1993, and 1997, respectively. He has been working with the Department of Management Information Systems, Chungbuk National University, since September 2000. He worked at ETRI as a Senior Researcher, from February 1997 to August 2000. His research interests include telecommunications management and information security economics. His recent research articles have appeared in international journals, such as *European Journal of Operational Research*, *ETRI Journal*, *Journal of the Operational Research Society*, *Operations Research Letters*, and *Stochastic Analysis and Applications*.

SOOCHANG PARK (Member, IEEE) received the Ph.D. degree from Chungnam National University, South Korea, in 2011. He was with The Hong Kong University of Science and Technology (HKUST) as a Research Associate, in 2016. He worked with the Institut Mines-Telecom, Telcom SudParis, France, as a Research Engineer, from 2013 to 2015, and was with Rutgers University, USA, as a Postdoctoral Researcher, in 2012. He has been an Associate Professor with the Department of Computer Engineering, Chungbuk National University, since 2017. His research interests include networking technologies, sensing and data analytics, mobile, and the Internet of Things-based smart applications.