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Adaptive Channel Assignment With Predictions of Sensor Results and Channel Occupancy Ratio in PhyC-SN

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ABSTRACT Applications related to the Internet of Things are widely diversified and require both low latency and the access of massive sensors to wireless sensor networks. In physical wireless parameter conversion sensor networks (PhyC-SN), a fusion center (FC) can recognize information from all sensors on the frequency spectrum of the received signals via conversion from sensor information to signal frequency. The higher resolution of sensor information of PhyC-SNs requires securing more frequency bandwidth. Therefore, spectrum sharing between PhyC-SNs and other systems is essential. For this study, we assume that primary systems (PSs) refer to other wireless systems and that secondary systems (SSs) refer to the PhyC-SN. The SS detects any access from the PS and immediately stops access to an FC. This results in a loss of sensor information. Thus, the accuracy of the gathered sensor information by an FC is degraded. This paper proposes an adaptive channel assignment based on two predictions; sensor information and channel occupancy rate. In the proposed method, the predicted error caused by the cessation of channel access is calculated and the assignment is constructed by minimizing this predicted error. Since the sensor can select channels in accordance with the error of an instantaneous sensor result, the proposed channel assignment can utilize awareness of the instantaneous sensor result. The proposed method achieves high accuracy of gathered sensor information while delivering less frequent sensor information to the FC, thereby improving the utilization efficiency of frequency channels.

INDEX TERMS Channel occupancy rate, dynamic spectrum access, minimum cost flow problem, optimal resource assignment, wireless sensor networks.

I. INTRODUCTION

Recently, the Internet of Things (IoT) has attracted increasing attention for the purpose of monitoring and controlling the status of computerized devices using the Internet, thereby realizing possible improvements in convenience, productivity, and energy efficiency [1]. The demands of the data transmission networks that support the IoT, known as Wireless sensor networks (WSNs), have thus greatly diversified over recent years. Fields of particular interest include; reducing maintenance costs via ''life extension'' [2], ''low delays'' for mechanical robot control and autonomous driving [3], [4], and a ''high capacity'' for gathering wide and diverse sensor information, such as the monitoring of crustal movement during earthquakes [5]. Since WSNs involve machine to machine (M2M) communication, the demand for WSNs is likely to become significantly enhanced as compared to conventional wireless communication, which involves human to machine communication.

To achieve real time properties and a high capacity to access multiple sensors of WSNs, several wireless access schemes have been implemented. Frequency hopping methods [6] and the use of ultra-wide bands based on impulse radio time hopping [7] enable simultaneous wireless access based

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on spread spectrum technology. However, when the load from the simultaneous wireless access of sensors exceeds the spreading gain, the packet error rate rapidly degrades, which can drastically degrade communication quality. Methods involving multi-user, multi-input, multi-output [8] and non-orthogonal multiple access [9] technologies also enable the simultaneous wireless access of multi-antenna systems. However, such methods cause increases in delay times owing to the complicated processing required for separation of a signal.

The present authors have proposed the use of Physical Wireless Parameter Conversion Sensor Networks (PhyC-SNs) as novel, real time information gathering systems [10]. A PhyC-SN converts sensor information to a carrier frequency in a manner similar to frequency shift keying. After all sensors in the network simultaneously access a single fusion center (FC), the FC detects the frequency spectra of the received signals using fast Fourier transform (FFT). In this case, the modulation signal sent by each sensor appears as a sharp spike in a spectrum at different frequencies, where the center frequency of the spectrum corresponds to the sensor information. Since distribution of the spectra coincides with that of all sensor information, the statistical information (such as the median value and the variance of the distribution) is instantly obtained. The processing delay in the demodulation at the FC is extremely short, as it simply consists of a one-time FFT and spectrum detection. After obtaining the statistics for all sensors, the FC can separate the signals by using a few features from each sensor as information sources. For example, we have proposed a method using the unique frequency offset of a sensor [11], [12], a method using the Kalman filter for capturing temporal correlations of sensor results [13], and a data separation method that regards the correlation of data as a shortest path problem [14].

A PhyC-SN determines the number of quantization levels for sensor information based on available bandwidth, meaning that the transmission of highly detailed sensor information requires expansion of the bandwidth. For such an expansion, the network utilizes a dynamic spectrum access (DSA) cognitive radio, which allows frequency sharing between different types of radio systems. For example, the 2.4GHz band uses WiFi, ZigBee, and BLE, and the Sub-GHz band, WiSUN and LPWA, share a frequency spectrum among heterogeneous wireless systems. To avoid interference with other systems, a listen before talk (LBT) access control is applied using a spectrum sensor. When access from another system is recognized, the external access of the main system is stopped, thereby avoiding interference with other systems. Hence, transmitting opportunities for the main system are somewhat limited when other systems frequently use the same channels. In the PhyC-SN, each quantization level of sensor information is assigned to a particular channel for modulation and demodulation.

If any channels are frequently occupied by other systems, the quantization levels assigned to them frequently fail owing to the LBT access control. As a result, the accuracy of the statistics obtained from the aggregated results of all sensors is drastically degraded. Therefore, the construction of assignments between quantization levels and channels should include adaptation to channel occupancy caused by the other systems.

In this paper, we propose using an adaptive construction to assign channels to quantization levels in PhyC-SNs by utilizing two predictions, sensor information and channel occupancy rate (COR). The first is that information from sensors that captures physical phenomena such as temperature, illuminance, humidity, vibrancy, location, and CO^2 density has significant temporal and spatial correlation. We propose a probability model to estimate future sensor information derived from the aggregated results of past sensor information. As a result, an occurrence probability is obtained from the quantization levels of that sensor information. Second, we focus on the COR of each channel [15], which is the average frequency of use by other systems. The COR is given as the ratio of the entire spectrum sensor observation time to the time another system occupies a channel and can therefore indicate the probability that a channel will be occupied in the future. Using the two predicted values we construct a method of assigning channel and quantization levels based on cost optimization.

We consider two types of cost: the successful probability of delivering (SPD) sensor information to the FC and the minimum mean square error (MMSE). For the cost associated with MMSE, the predicted error caused by the cessation of channel access is calculated and assignment is decided by minimizing this predicted error. Since the sensor can select a channel in accordance with the error of an instantaneous sensor result, the proposed channel assignment uses awareness of the instantaneous sensor result. This paper also considers double stage recognitions (online and offline processes) for an assignment optimization method. The online and offline processes estimate the statistics of all the sensor information and a future tendency for each sensor result. We consider two schemes for estimating COR: the use of specific spectrum sensors and crowd-sourced [16] consignment of other wireless systems. For computer simulation and experimental evaluation, the proposed PhyC-SN achieves the superior accuracy that aggregated sensor information brings, compared with conventional packet access based on frequency division multiple access (FDMA). Moreover, the method of assigning channels and quantization levels, which is constructed using the MMSE criterion, improves the accuracy of aggregated sensor information with a smaller SPD owing to the awareness of the instantaneous sensor result. Thus, it can improve the usage efficiency of frequency channels.

The contribution of this study is as follows. First is the construction of a wireless sensor network with channel assignment based on the two predictions, sensor results, and an estimation of COR assisted by spectrum sensor and crowdsourcing. Second is the construction of channel assignment using recognition of the instantaneous sensor result. The third

TABLE 1. Abbreviated words.

IoT	Internet of Things
WSNs	Wireless Sensor Networks
PhyC-SNs	Physical Wireless Parameter Conversion Sensor Networks
FC	Fusion Center
FFT	Fast Fourier Transform
DSA	Dynamic Spectrum Access
LBT	Listen Before Talk
COR	Channel Occupancy Rate
SPD	Successful Probability of Delivering
MMSE	Minimum Mean Square Error
FDMA	Frequency Division Multiple Access
QoS	Quality of Service
PDR	Packet Delivery Rate
PS	Primary System
SS	Secondary System
CCI	Co-Channel Interference
CSI	Channel State Information
IFFT	Inverse Fast Fourier Transform
CM	Conversion Matrix
RMSE	Root Mean Square Error
MSE	Mean Square Error

TABLE 2. Parameters in this paper.

J	The number of nodes
N	The total number of quantization levels
K	The total number of subcarriers
Δ	The quantization interval
S_d	The maximal distance of spectrum sensor from the node
Δ_{S_d}	Parameter for deciding the maximal difference of sensitivity

clarifies the advantage of the proposed channel assignment using computer simulation.

The production of cognitive sensor networks and the optimization of channel assignment are provided in Section II. The assumed system model and details of the proposed channel assignment are provided in Section III. The simulation results are provided in Section IV. Section V concludes this paper. Tables 1 and 2 show the list of abbreviated words and parameters in this paper, respectively.

II. RELATED WORKS

Various DSA schemes for WSNs have been considered using frequency spectrum sharing among heterogeneous wireless communication systems. Spectrum sharing causes the degradation of specific quality of service (QoS) criteria, such as the packet delivery rate (PDR), latency, and the accuracy of the aggregated sensor information [17]. Therefore, an important problem concerning spectrum sharing is how to improve the degraded QoS.

In spectrum sharing among heterogeneous wireless communication systems, it is assumed that there are two priority classes in the access channel: Primary systems (PSs) and Secondary systems (SSs). In order to increase the number of simultaneous accessing nodes, both PSs and SSs simultaneously access the frequency spectrum without the degradation of QoS, which is referred to as an underlay DSA [18]. The co-channel interference (CCI) from the transmitters of the PS is derived using the theory of stochastic geometry and the optimal construction of transmission power control of the SS is constructed as in [19]. In an underlay type of DSA, the instantaneous CCI of the PS fluctuates significantly and is dependent of the PS traffic. A power margin [20] or a high-speed MAC protocol is required, which estimates the instantaneous CCI of the PS and controls the parameters of transmission power and wireless access. However, this causes excessive power consumption by the sensor nodes.

In underlay DSA, the transmission power is too small to suppress interference to the PS and to maintain the large throughput required for QoS of the SS. When the SS can transmit a signal with enough power to satisfy the required QoS, it controls the selection of accessing channels or the access timing to a channel to avoid harmful interference to the PS, where the type of spectrum sharing is an overlay DSA. Various varieties of channel selection or resource allocation for overlay DSA of cognitive sensor networks have been considered so far [21]. Reference [21] shows conventional studies for optimal channel assignment based on various kinds of criteria, such as energy efficiency, throughput, QoS, interference avoidance, fairness or priority, and the number of handoff events. For our proposed WSNs, the amount of information from sensors is constant and two aspects of quality are achieved; that is the real-time data collection for simultaneous access from all the sensors to the FC and avoiding interference to the PS. In addition, the accuracy of all the sensor results collected by the FC is adequately improved. Conventional studies consider maximization of the PDR for improving the accuracy of sensor results collected by FC. Random channel assignment to a sensor node in FDMA systems is proposed [22]. Since interference to the PS can be modeled using the stochastic process, the transmission power is controlled to ensure the suppression of interference to the PS. However, the optimization of channel assignment is not considered. Channel assignment based on spectrum usability for increasing PDR and reducing power consumption is proposed [23]. Carrier sensing is iteratively performed until an available channel is found and thus the delay for channel access is significant. Channel assignment with an awareness of the transmit waiting time of each sensor is proposed [24], but is only available under an unbalanced transmit waiting time among sensors. Channel assignment for increasing the efficiency of both energy and frequency spectrum usage with the securement of a specific PDR is proposed for the WSN via energy harvesting [25]. If channel access from the PS increases, the required PDR cannot be assured. Channel assignment using a successful rate of packet transmission based on the signal to noise power for minimizing late packet delivery is proposed [26]. This requires channel state information (CSI), but how to estimate CSI is not described. The optimal channel assignment subject to cumulative interference for maximizing the availability of a channel is considered [27]. In addition, channel assignment based on the COR of a PS assisted by a cloud server for maximizing the future availability of access channels is considered [28].

The conventional channel assignment for maximizing PDR is via assignment to an individual sensor node. In PhyC-SN, the channel assignment to the individual quantization level of a sensor result is constructed, and thus, each sensor changes the accessing channel in accordance with the importance of the instantaneous sensor result. Channel assignment by adaption to an instantaneous sensor result is referred to as channel assignment with information awareness. To our knowledge, channel assignment with information awareness has not yet been considered.

Moreover, tendencies found using sensor information have recently been applied to WSN protocols to reduce power consumption and improve the accuracy of gathered sensor information. Coding schemes that include the temporal and spatial correlations of sensor information have been considered for improving both error rates [29] and the efficiency of collecting sensor information owing to the suppression of redundant data [30]. A sleep schedule using the temporal correlation of sensor information has been proposed for prolonging the life time of sensors [31]. For a multi-hop WSN, a clustering technique using the spatial correlation of sensor information is proposed in [32]–[34]. As the updating of clustering becomes less frequent, overhead signaling for rearranging clusters is reduced, achieving the prolongation of sensor nodes. In addition, the access schedule of sensor nodes based on the spatial correlation of sensor information is proposed in [35]. The improvement in the QoS achieved; more specifically the latency, the accuracy of gathered sensor information, and the power consumption of sensor nodes are all enhanced.

However, the achievement of real-time information collection using sensors together with the construction of channel selection based on the tendencies of both sensor information and channel occupancy rates has not yet been considered. Thus, this paper utilizes a novel WSN for achieving real-time data collection and improving frequency usage efficiency under a frequency spectrum shared among heterogeneous wireless communication systems.

III. SYSTEM MODEL

A. OVERVIEW OF PHYC-SN

Figure 1 shows an overview of the proposed PhyC-SN. The system is made up of single FC and multiple sensor nodes (nodes); each node sends detected sensor information to the FC. Hence, a star network topology is constructed, where j indicates the node number ($j \in \{1, 2, \ldots, J\}$) and J is the total number of nodes.

In each node, sensor information is converted into a discrete value using uniform quantization, where the delegated value of each quantized interval is referred to as a quantization level. We define $x_{j,n}, n \in \{1, 2, \ldots, N\}$ as the nth quantization level of the jth node, where N is the total number of quantization levels. In the PhyC-SN, the quantization level

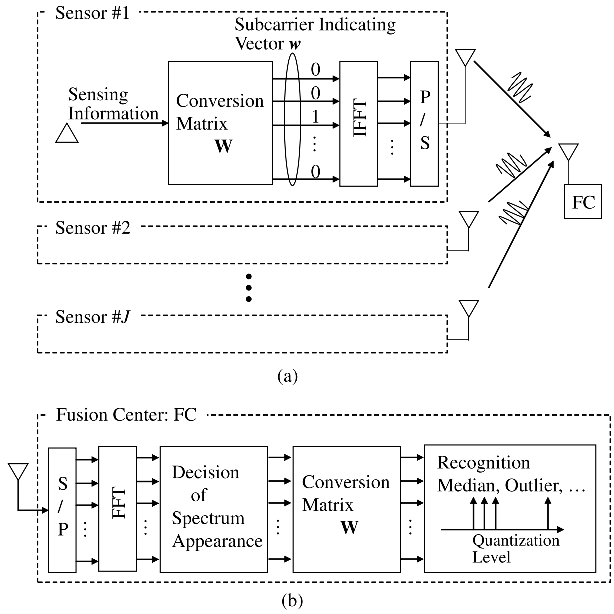

FIGURE 1. Overview of PhyC-SN.

is converted to subcarrier by inverse fast Fourier transform (IFFT). The PhyC-SN uses a conversion matrix $\mathbf{W}$ to determine the relationship between the quantization level and the subcarrier number. If nth quantization level is converted into kth subcarrier, the conversion matrix components of the kth line and nth column, $W_{k,n}$, are set to 1, $W_{k,n} = 1$. Otherwise, $W_{k,n} = 0$.

The conversion matrix has the following two conditions of constraint: (1) Each quantization level must be converted into a subcarrier. Therefore, $\sum_{k=1}^{K} W_{k,n} = 1$ is set, where K is the total number of subcarriers. (2) Each subcarrier is assigned to (at most) one quantization level. It is acceptable for a subcarrier to not be assigned to any quantization level. Therefore, $\sum_{n=1}^{N} W_{k,n} \leq 1$, where $N = K$, the equal relation, $\sum_{n=1}^{N} W_{k,n} = 1$, is set.

As example, we set a conversion matrix with K lines and N columns. As a result, the above two constraint conditions are described as follows:

$$\mathbf{W} \in \{0, 1\}^{K \times N} \quad \text{s.t.} \begin{cases} \sum_{k=1}^{K} W_{k,n} = 1 \\ \sum_{n=1}^{N} W_{k,n} \leq 1. \end{cases} \tag{1}$$

where the matrix is referred to as a conversion matrix (CM). For sharing the conversion matrix, the FC broadcasts information pertaining to the CM to all nodes.

If a nth quantization level is converted via subcarrier modulation, the node selects the nth column vector of the CM, $\mathbf{W}_n = [W_{1,n}, W_{2,n}, \ldots, W_{K,n}]^\top$, after which it is fed into the IFFT. Following this, the node obtains the time domain signal of a subcarrier whose frequency corresponds to the nth quantization level. After frequency up-conversion, the sinusoidal wave of the carrier frequency plus the subcarrier frequency are sent to the FC.

The FC broadcasts a request signal to all sensors and all nodes simultaneously send the resulting sinusoidal waves to the FC. Thus, the request signal sent by the FC is a trigger for the access channels of all nodes.

After down conversion, the FC detects the frequency spectrum of the received signal by FFT. The sinusoidal wave sent by each node is detected in the narrow spectrum in the form of a spike [13]. Since the size of the IFFT used by the sensor is the same as that of the FFT used by the FC, the spectrum of received signal is resolved into the common spectrum components of the subcarrier. If the FC detects spectrum components above a certain threshold, it recognizes the subcarrier index of the detected spectrum components. Following this, the FC can recognize all sensor information via conversion from the recognized subcarrier indices to the quantization level of sensor information by the CM, **W**. As a result, the FC can recognize the statistical tendencies of the aggregated sensor information. The threshold for detecting spectrum components should be adjusted in order to avoid misdetection and false alarms [36]. The impacts of both false alarms and misdetection to the accuracy of aggregated sensor information are important topics for future work; thus, this paper assumes that neither situation has occurred due to use of a suitable threshold. In addition, the frequency offset caused by the frequency mismatch of local oscillators between the transmitter and receiver can cause errors in the recognition of sensor information and inter-carrier interferences [13]. Compensation techniques for frequency offset, such as multi-antenna schemes [13] and interference cancellation [11], [12], have been considered. This paper assumes that any frequency offset is negligible owing to these compensation techniques.

Once the FC can estimate the median, deviation, and outliers of all sensor information from the detected spectrum components, various schemes for inserting the ID node into the transmitted signal are considered for specifying the information source of the individual sensor information. These include frequency hopping with ID specific sequences [37], fractional frequency offset with ID specification [11], [12], and multi-target tracking with periodically informing ID [14].

B. SPECTRUM SHARING AMONG PHYC-SN AND OTHER SYSTEMS

We assume that the PhyC-SN utilizes an LBT type of DSA such as WiFi, and that PS and SS refers to other systems and the PhyC-SN, respectively. PSs and SSs are located at random points over a specific area. In the PhyC-SN, a node detects the access of a PS via a spectrum sensor in a channel. When the node detects access, it stops accessing the channel; the channel bandwidth is identical to the subcarrier bandwidth defined by the FFT and the channel number is the same as the FFT index. As a result, the node cannot inform the FC about the sensor information.

The availability of spectrum sensors for detecting PSs is defined by the circle model [38]. If a PS is located within the circle of a spectrum sensor, a SS can recognize the access of the PS; otherwise it cannot. We assume that interference from an SS to the PS within and without the circle of a spectrum sensor is large and small enough such that PS packet loss either occurs or does not occur, respectively. Therefore, the SS can avoid harmful interference to the PS within the circle of the spectrum sensor, as well as performing the spatial reuse of the channel accessed by the PS outside the circle of spectrum sensor.

Error detections, false alarms, and misdetection have all occurred during spectrum sensing [36]. For suppressing error detections, the enhancements of spectrum sensing have been studied [39]. Since the impact of false alarms and misdetection to the sharing of spectra by the PhyC-SN is important for future work, we assume that this does not occur in this instance.

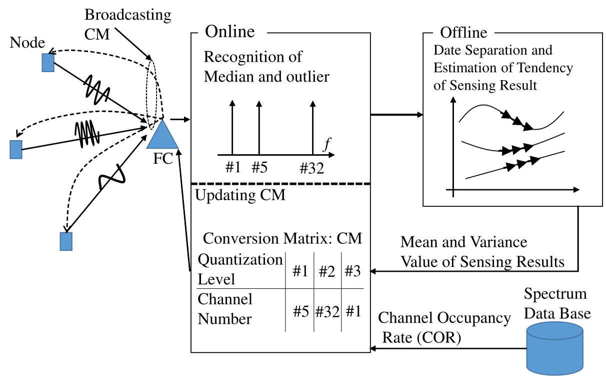

FIGURE 2. **Double stage recognition for proposed channel assignment.**

IV. PROPOSED CHANNEL ASSIGNMENT

The proposed method must predict the tendency of sensor information and the COR. Figure 2 shows the application of the proposed method for predicting two tendencies, referred to as double stage recognition. The two external sources for the prediction of COR are analyzed and detailed in section IV-B. The FC constructs the CM for determining assignment of quantization level and channel using the two tendencies. Following this the FC broadcasts information related to the CM of the request signal to all sensors.

This section explains the prediction of the tendency of sensor information, the prediction of the COR with external sources, and the two types of CM construction methods.

A. DOUBLE STAGE RECOGNITION

Figure 2 shows the process flow of double stage recognition. In the first stage (online process), the FC recognizes the median, outlier, and deviation of all the sensor information using spectrum detection and the conversion from subcarrier index to sensor information. In the second stage, (offline process), the FC estimates the individual sensor information. Owing to the ID insertion [11], [37] and data tracking techniques [14], the FC can individuate all of the aggregated sensor information. In addition, the FC utilizes first in first out (FIFO) memories for recording the individual sensor information, where the number of memories are equal to the number of nodes. Techniques such as use of the Kalman filter [40], the autoregressive model (AR) [40], and use of the minimum mean square error (MMSE) [41] are used to predict the tendency of sensor information from previously recorded data.

Owing to the predicted tendency of sensor information, the most likely value of sensor information and its deviation could be estimated by extrapolation. In mobile sensor networks for robotics, when information concerning spatial position is modeled using a random variable of Gaussian distribution, a highly accurate description of a robot's position can be achieved [42] . A Kalman Filter can predict the sensor information modeled by a random variable of Gaussian distribution with high accuracy [43]. When sensor information is determined by numerous various incidents, sensor information can be modeled using a random variable of Gaussian distribution in accordance with a central limit theorem [44]. We assume that future sensor information is modeled using a Gaussian random model whose average and variance are given by the most likely value of sensor information and its deviation.

When the mean and variance of the jth node's Gaussian model are predicted as μ_j and σ_j^2, the probability of the nth quantization level, $x_{j,n}$, is given as:

$$p_{j,n} = \int_{x_{j,n}-\Delta/2}^{x_{j,n}+\Delta/2} \frac{1}{\sqrt{2\sigma_j^2}} e^{-\frac{(x-\mu_j)^2}{2\sigma_j^2}} dx$$
$$= \frac{1}{2}\left[\mathrm{erfc}\left\{\frac{x_{j,n}-\Delta/2-\mu_j}{\sqrt{2\sigma_j^2}}\right\} - \mathrm{erfc}\left\{\frac{x_{j,n}+\Delta/2-\mu_j}{\sqrt{2\sigma_j^2}}\right\}\right], \quad (2)$$

where Δ is the quantizing interval and $\mathrm{erfc}(\cdot)$ is the complementary error function [45]. Thus, the FC could predict the occurrence probability of each quantization level for each node.

B. PREDICTION OF COR

From the assumed sensitivity of a spectrum sensor in section III-B, it is possible to detect the wireless access of different PSs even if each sensor is located in a different place. Therefore, the CORs measured by each sensor are also different [38].

The wireless architecture of the sensor node is a narrow band transceiver designed to ensure low power consumption and the use of simple processing [18]. As a result, the accessing channels of nodes are limited. To obtain the COR for all the channels, the switching channels and COR measurements are iteratively performed. As many channels are defined in the PhyC-SN, measurements of the COR and switching channels are numerous. The required power consumption for measuring COR is excessive, therefore we consider two external sources for measuring COR; specific spectrum sensors, and crowd sourcing to increase energy efficiency.

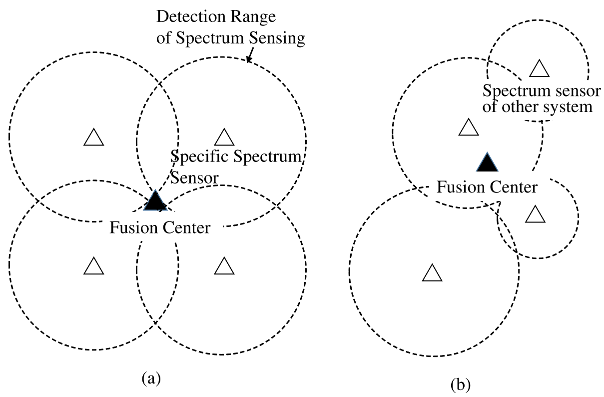

FIGURE 3. Image of position and sensor sensitivity of outsources for estimating COR. (a) Spectrum spectrum sensors. (b) Crowd sourcing.

1) SPECIFIC SPECTRUM SENSORS

A specific spectrum sensor has a solo function, which is the measurement of the COR. Figure 3 (a) shows the location and sensitivity of specific spectrum sensors. Each spectrum sensor measures the COR of all channels and informs the FC of both the measured COR and its positional information, where specific sensors can obtain position information via positioning systems (such as GPS).

Each node in the PhyC-SN also informs the FC of positional information, obtained via positioning systems. The FC considers the COR of the node as the COR of the nearest specific sensor to the node. Thus, the difference between the COR obtained with a specific sensor and that measured by the node occurs due to their different positions. As the number of specific sensors increases, the COR difference can be mitigated. In addition, since the specific sensors are systematically located, it can be mitigated rapidly as the number of sensors increases. The sensitivity of the spectrum sensors is switchable depending on their intended use and can be set to the same value as the PhyC-SN sensors.

2) CROWD SOURCING SCHEME

We assume that the other systems use spectrum awareness of cognitive radio for exploiting vacant channels. The COR information is useful for the PhyC-SN but not for the other systems. Therefore, exchanges regarding information concerning COR between PhyC-SNs and other systems is encouraged. If the other systems are crowded around a PhyC-SN, the PhyC-SN can gather comprehensive information about the COR [16]. We refer to the COR measurement by other systems as crowd sourcing.

In crowd sourcing, the other systems inform the FC regarding the measured COR and positional information. The FC can presume the COR of the node as equal to that of the nearest other system to the node. Moreover, crowd sourcing is free from the cost of constructing and running spectrum sensors.

Since the location of a spectrum sensor is not controlled, the spatial density of the sensors is not uniform. In addition, the sensitivity of each spectrum sensor is adjusted as each system exploits more channels [20]. Mismatches in position and sensitivity between the PhyC-SN and other systems occur. The former mismatch can be compensated for by increasing the number of systems, but the latter cannot.

C. OPTIMAL CONSTRUCTION OF A CONVERSION MATRIX

After second stage recognition, the FC obtains two predictions: the probabilities of quantization levels in the sensor information and the COR. The FC constructs the CM, $\mathbf{W}$, using a two-stage optimization system, the maximal successful probability of delivering sensor information, and the MMSE.

1) MAXIMAL SUCCESSFUL PROBABILITY OF DELIVERING SENSOR INFORMATION (SPD)

The jth node sends the nth quantization level to the FC by sinusoidal wave whose frequency is matched to the kth channel. Once this occurs, the SPD of the sensor information is $p_{j,n}(1-\rho_{j,k})$, where $\rho_{j,k}$ is the COR of the kth channel measured by jth node. Therefore, the CM, $\mathbf{W}$, is constructed from the following maximization problem:

$$\max_{\mathbf{W}} \sum_{k=1}^{K}\sum_{n=1}^{N} W_{k,n} \sum_{j=1}^{J} p_{j,n}(1-\rho_{j,k}) \tag{3}$$

Subject to

$$\sum_{k=1}^{K} W_{k,n}=1, \quad \sum_{n=1}^{N} W_{k,n} \leq 1. \tag{4}$$

This is known as the maximal flow problem. If $K = N$, the candidate solutions of this problem have $O(N!)$; thus, it is an NP hard problem.

This problem corresponds to the assignment problem[1]; doing so is known to result in the maximum matching problem for the bipartite graph and also in a minimum-cost flow problem that can be efficiently solved by using a Hungarian algorithm (also known as the Kuhn-Munkres algorithm [46], [47]). In the proposed method, we use an implementation of $\mathcal{O}(N^3)$ computational complexity shown in [48], which is based on the graph theory (the minimum-cost flow problem) [49], [50].

2) MINIMUM MEAN SQUARE ERROR (MMSE)

When the jth node stops delivering the sensor information to the FC due to PS access, the FC ceases obtaining sensor information from the jth node. However, it can compensate by using the most likely sensor information value μ_j, which is predicted using past sensor information. If the jth node tends to deliver the nth quantization level of sensor information to the FC, the square error between the true and compensated quantization levels is $(x_{j,n}-\mu_j)^2$. The probability that jth node will detect PS access through the kth channel using a spectrum sensor is $\rho_{j,k}$. Therefore, the mean square error is given as: $(x_{j,n}-\mu_j)^2\, p_{j,n}\rho_{j,k}$. We construct the CM from the following MMSE:

$$\min_{\mathbf{W}} \sum_{k=1}^{K}\sum_{n=1}^{N} W_{k,n} \sum_{j=1}^{J} (x_{j,n}-\mu_j)^2\, p_{j,n}\rho_{j,k} \tag{5}$$

Subject to

$$\sum_{k=1}^{K} W_{k,n}=1, \quad \sum_{n=1}^{N} W_{k,n} \leq 1, \tag{6}$$

This is a known as the minimum cost flow problem, which is a linear programing problem. If $K = N$, the candidate solutions of this problem are $O(N!)$; thus it is an NP hard problem. Since this optimization is also applied to the Hungarian algorithm [46], [47], we obtain the optimal weights under $\mathcal{O}(N^3)$ computational complexity. In the channel assignment based on the MMSE, each sensor can adaptively select a channel in accordance with the square error of the instantaneous sensor result from the prediction. Therefore, channel assignment based on the MMSE uses awareness of the instantaneous sensor results.

V. NUMERICAL RESULTS

We verify the efficacy of our proposed method by computer simulation. The computer simulation is based on the Monte Carlo Method [54] and it is constructed by MATLAB. For construction of the optimal channel assignment, we use open source software [48]. Table 3 shows the simulation parameters.

TABLE 3. Simulation parameters.

Number of total channels, K,	64
Location of sensor nodes	2000 Square Mode
Sensitivity of Spectrum Sensor in Node	Circular model with $S_d = 800$ radius
Number of PSs	30
COR of PS	Random variable of [0,1) uniform distribution
Number of channels occupied by a PS, N_{PS}	8
Number of SSs	10
Number of total quantization levels, N	64
Size of memory for predicting sensor information	100 samples

We assume a square field for location of the sensor nodes. The FC is located in the center of the square. The position of each sensor is decided using the two-dimensional random variable of uniform distribution. Moreover, we assume the number of channels, K, is equal to the number of quantization levels, N. The maximum and minimum quantization levels of sensor information are $N/2$ and $-N/2+1$, respectively, using

[1] The assignment problem can be solved even with a more standard simplex method by relaxing the binary constraint $W_{ij} \in \{0, 1\}$ to the soft constraint, $W_{ij} \in [0, 1]$ because the solution matrix has a totally unimodular property. A global optimal solution matrix is solved by the more standard simplex method [51]. We can use general solvers, e.g., GROBI [52] and MATLAB [53], to solve this problem.

uniform quantization. We assume that the sensor information is modeled using a random walk before quantization. The original sensor information of the jth user in the ith sampling period, $q_j^{(i)}$, is given as follows:

$$q_j^{(i)} = \overline{\mu_j^{(i)}} + n_j^{(i)}, \tag{7}$$

where $\overline{\mu_j^{(i)}}$ is a real value from sensor information and is given as follows.

$$\overline{\mu_j^{(i)}} = \begin{cases} \overline{\mu_j^{(i-1)}} + \delta & \mathrm{mod}(i, 5) = 0 \\ \overline{\mu_j^{(i-1)}} & \mathrm{mod}(i, 5) \neq 0 \end{cases} \tag{8}$$

where mod(a, b) computes a modulo b and δ is the uniform random variable taking either 1 or -1. The initial value of the original sensor information, $\mu_j^{(i=1)}$, is modeled as the $[-0.2N, 0.2N]$ uniform random variable. $n_j^{(i)}$ is an external force to the sensor and is modeled using the Gaussian random variable with 0 average and $\sqrt{10}$ deviation.

During quantization, the jth sensor obtains the quantization level $x_{j,n}$ of the sensor information as follows:

$$\arg_{x_{j,n}} \min_{\forall n} \left(x_{j,n} - q_j^{(i)}\right)^2 \tag{9}$$

After quantization, each sensor sent the quantization level of sensor information to the FC via the PhyC-SN. We define the training period for predicting the tendency of sensor information as equal to the memory size. We do not evaluate the accuracy of the aggregated information from sensors during the training period. After completing the training period, we evaluate the accuracy of the aggregated information.

We assume that the bandwidth occupied by a PS is modeled by N_{PS} channels as a PS is a more broadband system than an SS. When constructing the proposed CM, we use a Hungarian Algorithm [48].

The FDMA is assumed to be a conventional access scheme. For the FDMA, the number of channels occupied by a node is set at 6 for fair comparison to the PhyC-SN, as the total number of quantization levels in the PhyC-SN is 64, which is equivalent to a 6-bit transmission. In addition, the FDMA uses a small order modulation scheme (similar to BPSK) to achieve the large propagation distance from the nodes to the FC. Thus, the data rates of the PhyC-SN and FDMA are common. The FDMA node continuously occupies 6 channels. As the total number of channels is 64, the number of nodes simultaneously accessing the FC is 10.

Two powerful channel assignments for the FDMA have been proposed. For the first, the adaptive channel assignment of FDMA for maximizing a SPD has been proposed [27], [28], where the SPD is the ratio of the number of packets successfully sent to the fusion center to the total number of packets. For the second, a random assignment between each sensor and channel has been proposed [22]. In the performance evaluations, the indicators of the former and the latter assignments are "FDMA Pmax" and "FDMA Random", respectively.

When using the PhyC-SN, the performance of random assignments between quantization level and channel, the optimal conversion matrix constructed by maximizing the successful probability of delivering sensor information, and the optimal CM constructed by the MMSE are labeled "random", "Pmax", and "MMSE."

For all four schemes, if the node does not deliver the sensor information to the FC via the channel occupied by a PS, the FC compensate by using the most likely value of sensor information predicted from previous data.

To evaluate the accuracy of the aggregated sensor information, we use the root mean square error (RMSE) as follows:

$$\mathrm{RMSE} = \sqrt{E_{j,i}\left[\left(\frac{\overline{x_j^{(i)}} - \overline{\mu_j^{(i)}}}{\Delta}\right)^2\right]} \tag{10}$$

where $\overline{x_j^{(i)}}$ is the quantization level of the jth user recognized by the FC in the ith time slot. The minimization of the RMSE value directly improve the recognition accuracy of the aggregated sensor information. If the RMSE $= 1$, the difference between the true sensor information and the gathered sensor information is equal to one quantization level Δ.

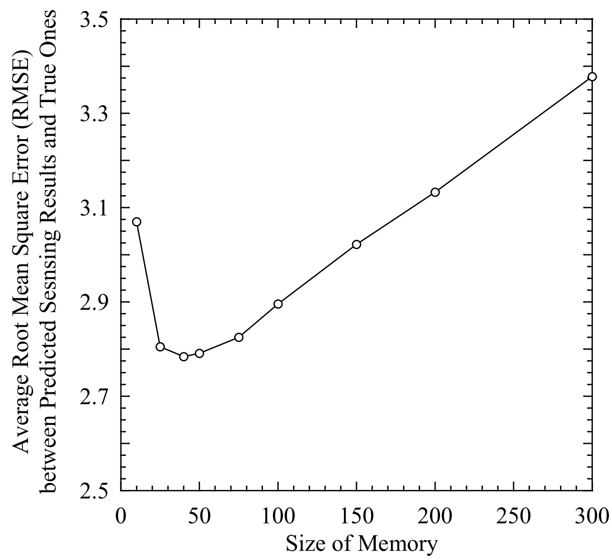

FIGURE 4. Performances between Size of Memory and Average RMSE.

In deciding the memory size for predicting the tendency of sensor information, we evaluate the average RMSE with various amounts of memory. Figure 4 shows the performance as indicated by the memory and the average RMSE, where we assume that all the sensor information has reached the FC without any access stop caused by the channel occupancy of a PS. From this figure, the convex tendency for size of memory is confirmed. This is because the tradeoff between mitigating the fluctuation of a sensor result and enhancing the tracking performance of sensor results is constructed for the amount of memory. The optimal memory for minimizing

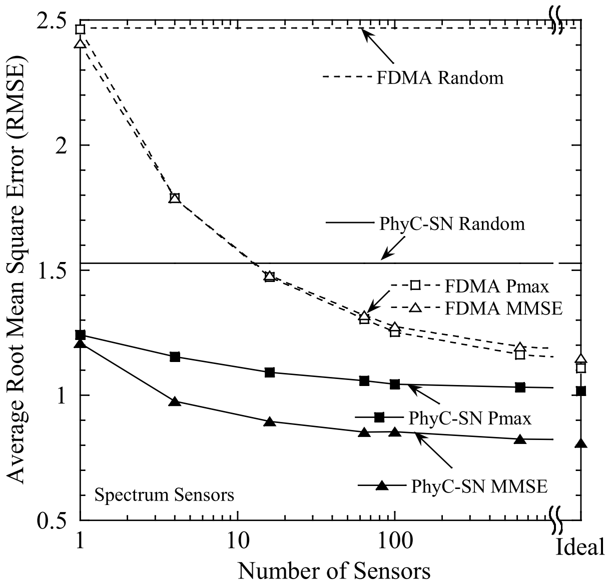

FIGURE 5. Performances of Average RMSE (Specific Spectrum Sensors).

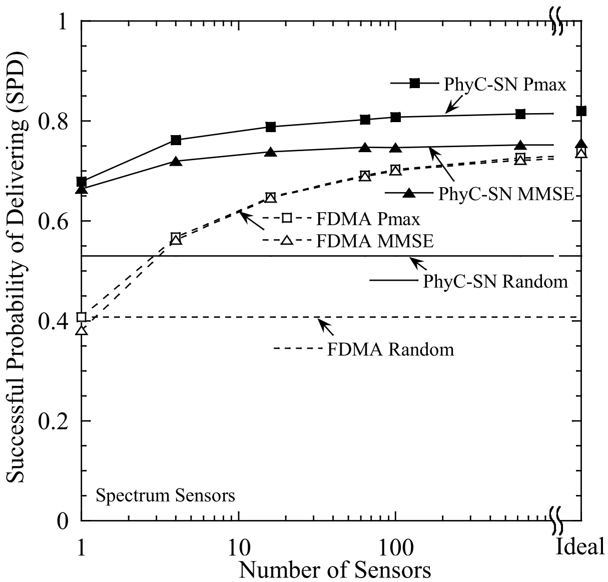

FIGURE 6. Performances of Average SPD (Specific Spectrum Sensor).

RMSE is from 30 samples to 75 samples and the average RMSE is not significantly different from this. Therefore, we use 50 samples as the memory size.

A. SPECIFIC SPECTRUM SENSORS

Figure 5 shows the RMSE of aggregated sensor information in a specific spectrum for estimation of the COR. "Ideal" in the horizontal axis indicates that the COR estimated by the spectrum sensor is perfectly matched to that estimated by the nodes. The area of sensor nodes is divided into small square grids and the specific sensor is then located on the center of each grid. Thus, the number of grids is equal to the number of specific sensors. Figure 6 shows the performance of the average SPD.

From figures 5 and 6, it can be seen that the RMSE and the SPD of FDMA are larger and smaller than those of the PhyC-SN, respectively. There are two reasons for the performance degradation of FDMA: the FDMA node occupies six times more channels than that of the PhyC-SN. When the PS accesses any channel occupied by the node, the node stops access to the FC. Therefore, the access of a node in FDMA is more frequently disturbed by the occupation of a channel by the PS. The second reason is the decreased freedom of channel selection. In the simultaneous access from all the nodes to the FC, almost all the channels are occupied. Although FDMA adaptively changes the assignment of a channel to each node under an ideal COR estimation, some nodes cannot avoid assignment to the channels highly frequently occupied by a PS.

The PhyC-SN MMSE and PhyC-SN Pmax achieve the smallest and second smallest RMSE. In particular, PhyC-SN MMSE achieves a smaller RMSE than the quantization interval. From these results, we confirm the advantages of the construction of an adaptive CM in the context of both sensor information and the COR. In addition, it is worth noting that in Fig. 6, the SPD of PhyC-SN MMSE is 5% smaller than that of PhyC-SN Pmax. Since PhyC-SN MMSE achieves superior RMSE performance with utilization of fewer channels, it can improve the usage efficiency of frequency resources. The reasons for this improvement are as follows. In PhyC-SN MMSE, it is not necessary to deliver the quantization level corresponding to the predicted mean value of the sensor information. Instead, the quantization level with a greater difference from the predicted mean value and higher occurrence probability is delivered to the FC as often as possible. Owing to the awareness of the instantaneous sensor results, the channel assignment based on MMSE can suppress redundant sensor information as well as achieve better accuracy of gathered sensor results.

As the number of specific spectrum sensors is greater than 64, we could not confirm large-scale improvement of the RMSE in PhyC-SN MMSE. Figure 7 shows the performance of the number of sensors and the mean square error (MSE) of an estimated COR from an ideal COR. From this figure, the performance of MSE is a monotone decreasing for the number of sensors because the location mismatch between the spectrum sensors and the sensor node is mitigated and thus the difference of an estimated COR is mitigated. In addition, as the number of sensors is larger than 64, the MSE of an estimated COR is smaller than $2 \cdot 10^{-2}$. Therefore, the required MSE of the estimated COR is almost $2 \cdot 10^{-2}$ or smaller. In the assumed environment, we consider the number of required specific spectrum sensors to be larger than 64.

B. CROWD SOURCING

For crowd sourcing, the location of the other systems for measuring COR is modeled using the two-dimensional random valuables of uniform distribution. We assume that the

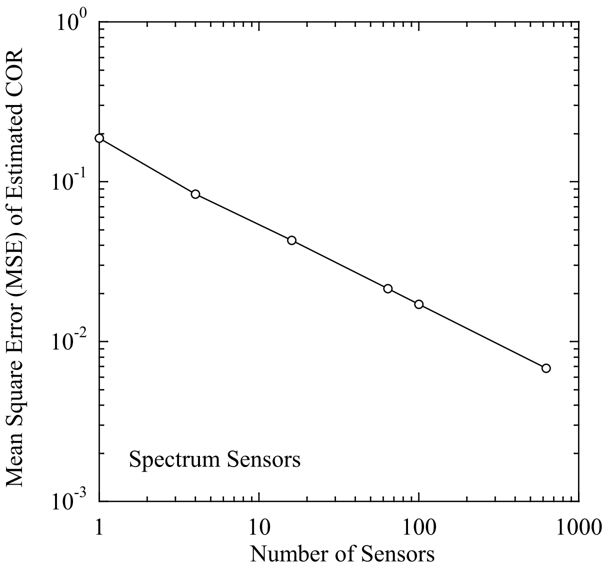

FIGURE 7. Performance between the number of sensors and the average MSE of the COR estimated by spectrum sensors.

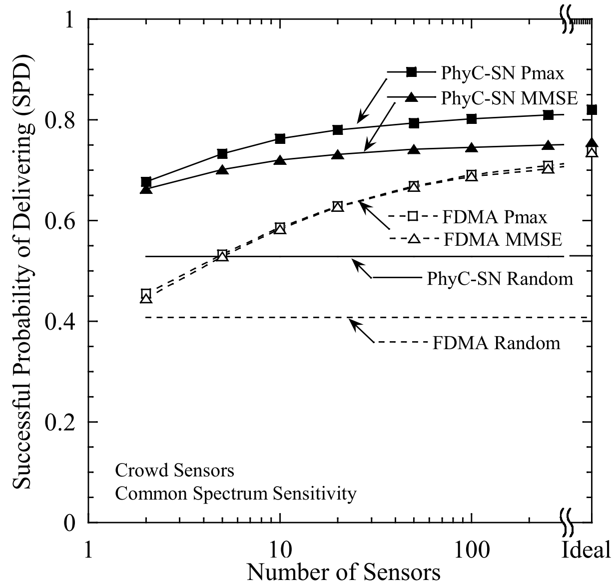

FIGURE 9. Performance of average SPD (Crowd Sourcing).

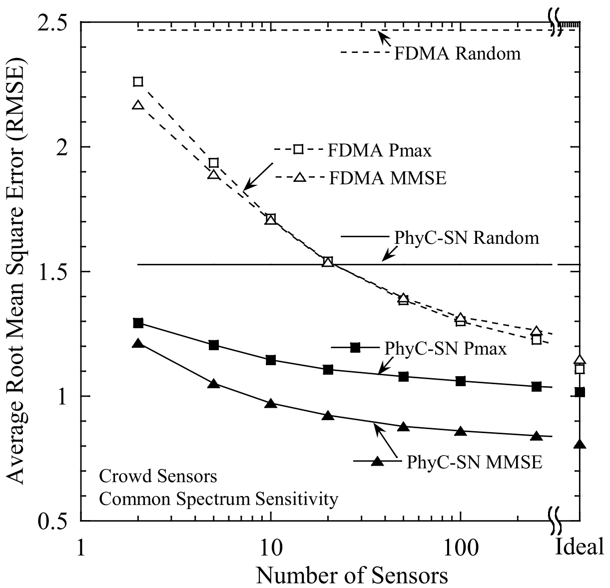

FIGURE 8. Performances of average RMSE in crowd sourcing.

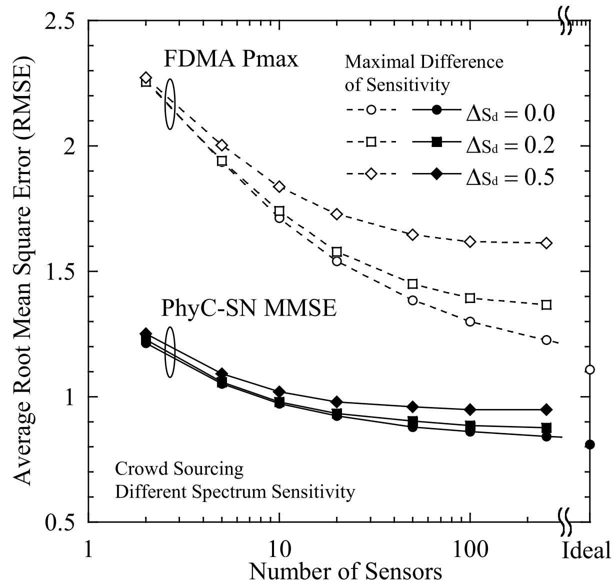

FIGURE 10. Performances of average RMSE (Crowd sourcing with different sensitivity).

sensitivity of a spectrum sensor in the other systems is identical to that of the PhyC-SN node.

Figures 8 and 9 show the performances of the RMSE and SPD and a number of other systems for measuring COR. As can be seen, the PhyC-SN MMSE achieves the minimum RMSE with a smaller SPD. Moreover, an improvement in frequency utilization is produced, even under the measurements of the crowd-sourced COR. Upon increasing the number of sensors, specific spectrum sensors converge slightly more rapidly to the RMSE than with crowd sourcing. This is because the specific spectrum sensors are located systematically, as the difference in distance between the node of PhyC-SN and a specific spectrum sensor decreases. This results in greater accuracy for estimating COR than with crowd sourcing.

Figure 10 shows the performances of RMSE and the number of spectrum sensors in crowd sourcing with different spectrum sensitivities. As described in section III-B, the sensitivity of spectrum sensor is modeled by a circle whose radius is defined by the maximal distance of PS access detection. We assume that the radius is modeled by the independent $[S_d(1 - \Delta_{S_d}), S_d(1 + \Delta_{S_d})]$, uniformly distributed random variable, where S_d and Δ_{S_d} are at the maximal distance of spectrum sensor from the node and the parameter for deciding

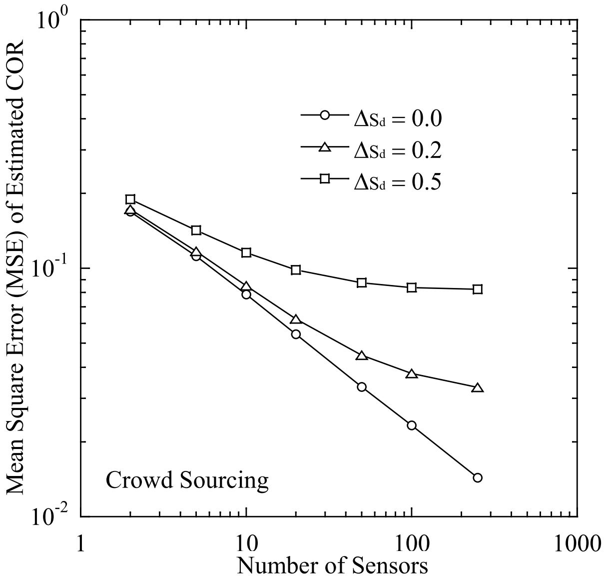

FIGURE 11. Performances between the number of spectrum sensors and average MSE of estimated COR (Crowd sourcing with different sensitivity).

the maximal difference of sensitivity is between the node and the spectrum sensor.

Figure 10 shows the performance between RMSE and the number of sensors in crowd sourcing, where Δ_{S_d} are 0, 0.2, and 0.5. The improvement of RMSE is confirmed despite spectrum sensitivity differences. However, as the number of sensors is larger than 64 in $\Delta_{S_d} = 0.5$, the RMSEs of both FDMA Pmax and PhyC-SN MMSE are not improved but saturated. Figure 11 shows the performance between the number of sensors and the MSE of estimated COR. From this figure, as the number of sensors is larger than 64 in $\Delta_{S_d} = 0.5$, the MSE of the estimated COR is also not improved. Therefore, non-improvment in estimating COR directly decides the degradation of the RMSE of sensor information. The RMSE of FDMA Pmax is more significantly degraded than that of PhyC-SN MMSE because the number of channels occupied by FDMA is 6 times larger than that of PhyC-SN and the cumulative estimation error of COR among 6 channels causes the degradation of channel assignment. Even in $\Delta_{S_d} = 0.5$, the RMSE of PhyC-SN MMSE is smaller than 1 and thus a smaller estimation error than one quantization level is achieved.

C. PERFORMANCE EVALUATION WITH ACTUAL SENSOR RESULTS

For the proposed assignment, the accuracy of the prediction of sensor results decides the accuracy of collected sensor results in the fusion center. Evaluating the accuracy of prediction to the practical sensor result is important for clarifying the practicality of the proposed assignment.

Figure 12 shows an overview of the performance evaluation composed of both the experimental environment and the

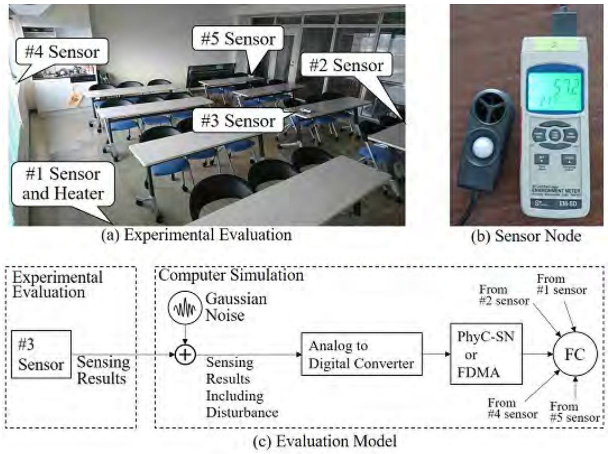

FIGURE 12. Overview of Experimental Evaluation and Computer Simulation.

TABLE 4. Computer simulation in part 2.

Number of total channels, K,	256
Location of sensor nodes	2000 Square Model
Sensitivity of Spectrum Sensor in Node	Circular model with $S_d = 800$ radius
Number of PSs	100
COR of PS	Random valuable of [0,1) uniform distribution
Number of channels occupied by a PS, N_{PS}	16
Number of SSs	5
Size of memory for predicting sensor information	100 samples
Number of Spectrum Sensors in Crowd Sourcing	50

computer simulation, where temperature sensors are used in the same evaluation system as Ref [12]. Temperature data is measured and recorded in the memory of each sensor. Following this, delivery of the measured sensor information to the FC by the WSN is performed via computer simulation. Therefore, we use the recorded temperature data as the test sensor result for use in the computer simulation.

Table 4 shows the simulation parameters of the WSN. Figure 13 shows the measured temperature data as a base certainty regarding sensor information.[2] We use a crowd sourcing scheme to measure COR, where the spectrum sensitivity in the nodes is equal to that in the crowd sourcing spectrum sensors. The measured temperature is added as the Gaussian noise, which is identical to that in eq.(7). The mean and variance of the Gaussian noise are 0 and 0.1. The dynamic range of the quantization level ranged from 0 to 51.2 degrees. The number of quantization levels was 256, which is equal to the number of channels.

Figures 14 and 15 show the CDFs of RMSE and SPD. The RMSE of PhyC-SN MMSE is the best RMSE and it achieves

[2]The data of figure 13 is commonly used as the test sensor result in [12] and [13]

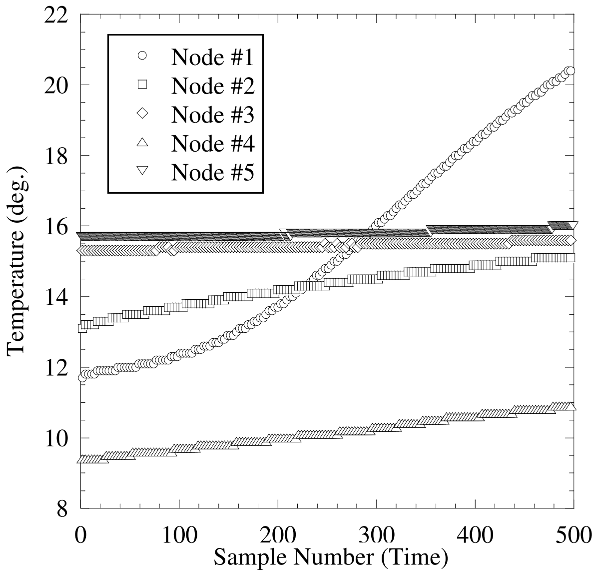

FIGURE 13. Ground Truth of Sensor Information (Temperature).

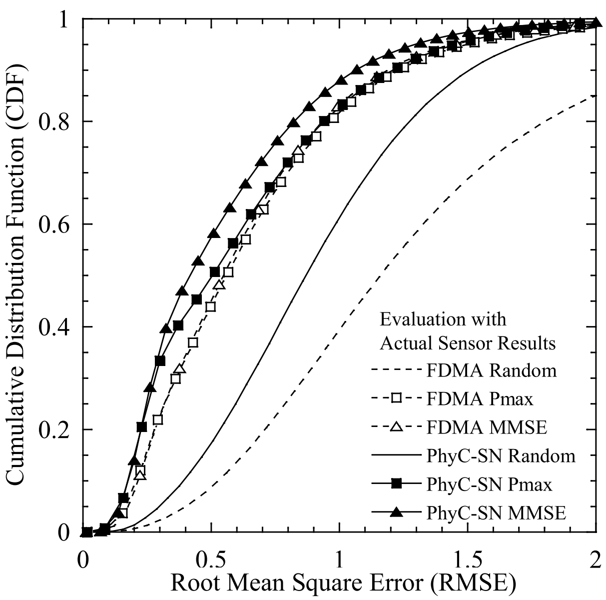

FIGURE 14. Performances of RMSE (Evaluation with Actual Sensor Results).

almost 90% for a RMSE under 1.0. In SPD performance, the PhyC-SN Pmax achieves the best SPD, but a larger RMSE than the PhyC-SN MMSE. The former cannot select the suitable channel for sending the sensor result with a large square error to the FC. The SPDs of FDMA MMSE and FDMA Pmax are smaller than that of PhyC-SN MMSE and Pmax. As we explained, FDMA occupies more channels than PhyC-SN. Therefore, FDMA more frequently stops sending the sensor results. When the PhyC-SN MMSE is applied to the practical detected sensor results, a better RMSE and

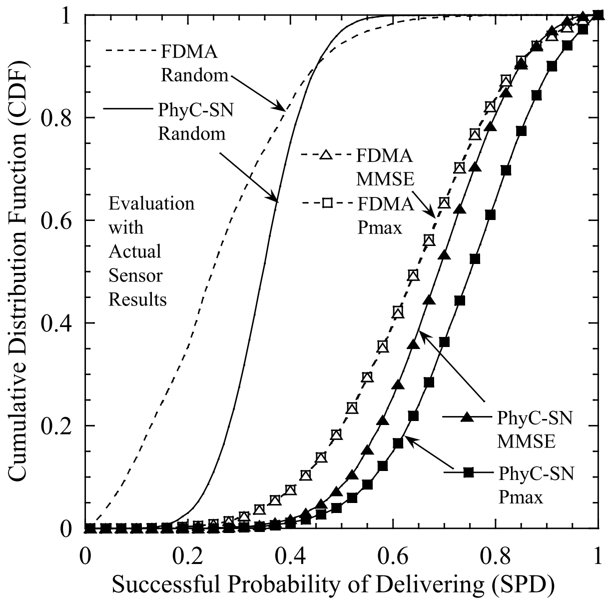

FIGURE 15. Performances of SPD (Evaluation with Actual Sensor Results).

smaller SPD are achieved and thus better frequency usage efficiency can be accomplished.

VI. CONCLUSIONS

This study implemented adaptive channel assignments for spectrum sharing among heterogeneous wireless systems in physical wireless parameter conversion sensor networks (PhyC-SN) under simultaneous wireless access from numerous sensors. In the proposed channel assignment method, the errors calculated from the predicted tendency of sensor information and predicted channel occupancy rate are minimized. The sensor adaptively selects the channel in accordance with the error from both the predicted sensor result and the actual one. Therefore, our proposed channel assignment uses an awareness of the instantaneous sensor results. From the computer simulation, the proposed channel assignment improves channel utilization efficiency.

In future work, the performance of our proposed method should be analyzed during real-time application of the Internet of Things.

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