Developing power control algorithms for dynamic multi-connection industrial wireless sensor networks

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ABSTRACT

In this paper, we propose a Dynamic Multi-Connection Industrial Wireless Sensor Network (DMC IWSN) model to improve data transmission efficiency in a factory workshop. We introduce a new power control algorithm called Window-Selection (WS), which adjusts sensor power based on predefined upper and lower limits. The algorithm reduces power when it exceeds the upper limit, increases power when it falls below the lower limit, and maintains power within these bounds. We compare the performance of the WS algorithm with the Max-Min (MM) algorithm, and a scenario no power control in terms of the weakest sensor capacity and total capacity in uplink transmission. Simulation results show that the WS algorithm achieves the highest capacities, while the MM algorithm moderately improves system performance in the DMC IWSN model.

Keywords: Wireless Industrial Sensor Network; Power control Algorithm; Window-Selection; Max-Min Algorithm.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) comprise numerous sensors connected wirelessly to collect, process, and transmit data to a central unit. They are widely used in fields such as environmental monitoring, smart agriculture, healthcare, and defense. Due to limited energy resources, WSNs require advanced power management solutions to extend their operational lifetime. Industrial Wireless Sensor Networks (IWSNs), a specialized type of WSN, are designed for reliable and low-latency operation in harsh industrial settings [1]. They are commonly used in production workshops to monitor processes and ensure safety. The proposed Dynamic Multi-Connection Industrial Wireless Sensor Network (DMC IWSN) model addresses challenges such as high interference and data loss in complex factory environments. By enabling sensors to dynamically connect to multiple access points (APs) and by applying advanced power control algorithms, the model optimizes transmission power, conserves energy, and enhances network scalability and real-time monitoring, making it suitable for Industry 4.0 applications.

In WSN models, particularly those used in factory production workshops, power control for sensors mounted on machinery surfaces is essential. Power control minimizes interference with surrounding devices, improves signal quality, and enhances capacity. Due to the adverse effects of factors such as dust, humidity, and noise on the transmission channel, sensors need to adjust their power levels accordingly: decreasing power when they are close to the AP or when channel quality is good in order to reduce interference, and increasing power when they are farther from the AP or when channel quality is poor to ensure effective data transmission. Throughout the research on power control solutions for WSNs, numerous algorithms have been proposed to enhance the operational efficiency of WSNs under varying conditions. To date, several power control techniques have been designed specifically for WSNs, including Distributed [2], Water-Filling [3], Fuzzy Adaptive [4], Game-Theory [5], Self-Learning [6], and Max-Min (MM) [7]. The Distributed algorithm is highly flexible and feasible but struggles to ensure global optimization. The Water-

Filling algorithm optimizes power allocation but requires detailed channel information. The Fuzzy Adaptive algorithm adapts well to dynamic environments, yet its performance heavily depends on the design of the fuzzy system. Game-Theory is suitable for systems with multiple interacting agents but necessitates in-depth knowledge and complex calculations. The Self-Learning algorithm can self-adjust over time but requires time to learn and stabilize. The MM algorithm improves the capacity of the weakest sensor but may reduce overall system capacity. Current power control techniques for WSNs in industrial settings include: optimal power control [8], which reduces interference but is computationally intensive; minimum transmission power control [9], which saves energy but may affect transmission quality; and dynamic power control [10], which quickly adapts to environmental changes but requires complex control mechanisms. In general, existing power control algorithms for WSNs in industrial environments face challenges in energy conservation, ensuring reliability under high interference, and adapting to diverse and dynamic networks, resulting in unstable performance. Selecting an appropriate power control algorithm for each specific WSN model remains a challenge.

In production workshops, sensors require stable connections to ensure uninterrupted manufacturing processes. Although the sensors are generally stationary and the data they collect seldom fluctuates, they are susceptible to interference from other machinery. Current power control algorithms for WSNs in industrial environments face challenges in optimizing energy consumption, integrating with existing protocols, ensuring reliability under high-interference conditions, and adapting to dynamic network variations, which leads to unstable performance [11]. Based on these observations, this paper makes two main contributions. First, we introduce a novel power control algorithm called "Window-Selection" (WS), which adjusts sensor power in real-time to enhance reliability and transmission efficiency. Second, the paper compares the performance of the WS algorithm with the MM algorithm. The signal processing procedures, algorithm details, simulation results, and evaluations are provided in the following sections to demonstrate the effectiveness of the proposed solution.The mathematical notations used in this paper are as follows: bold letters denote a column vector, the operator $()^*$ represents the conjugate matrix, $()^T$ denotes the transpose matrix, $()^H$ signifies the complex conjugate transpose matrix, $\|.\|$ is Euclidean norm and $\mathrm{E}\{.\}$ is expectation operators.

2. SYSTEM MODEL AND SIGNAL PROCESSING

2.1. System model

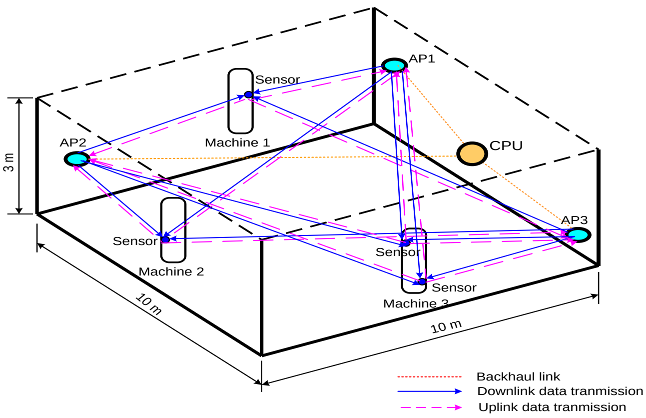

Figure 1. *DMC IWSN system model.*

Figure 1 illustrates the DMC IWSN model in a factory production workshop, where sensors mounted on the surface of machinery directly transmit and receive data from wall-mounted APs via wireless connections. Each sensor and AP is equipped with a single antenna, and the APs are connected to a Central Processing Unit (CPU) through a backhaul network.

The number of APs is denoted as *P*, and the number of sensors as *S*. The APs are synchronized using Time Division Multiple Access (TDMA) to ensure efficient, conflict-free data transmission. All APs are time-synchronized via protocols such as the Network Time Protocol (NTP) or Precision Time Protocol (PTP) to operate according to a predefined schedule. The sensors in the DMC IWSN model include temperature, humidity, vibration, pressure, and air quality sensors. The model utilizes an Ultra-Wideband (UWB) frequency, enabling precise positioning within centimeters and high-speed data transmission for real-time monitoring and rapid processing. Operating over a wide frequency band, UWB minimizes interference, ensures stable signals, reduces power consumption, extends sensor lifespan, and lowers operational costs. UWB performs efficiently even in environments with obstructions, making it ideal for production workshops [12].

The transmission channel vector between the p^{th} AP and the s^{th} sensor is denoted as g_{ps} and is determined using the following expression:

$$g_{ps} = \beta_{ps}^{1/2} h_{ps} . \tag{1}$$

In this context, h_{ps} represents the small-scale fading component. We assume that $\{h_{ps}\}, p = 1,...,P, s = 1,...,S$ is independent and identically distributed random variable. In practical scenarios, where sensors and APs are deployed within a small and confined space (e.g., production workshops), the impact of small-scale fading on the transmission channel vector is negligible. Consequently, we primarily focus on analyzing the influence of large-scale fading on the transmission channel vector g_{ps}.

The large-scale fading β_{ps}, denoted in equation (1), consists of two components: path loss and shadow fading, which are calculated using the following formulas:

$$\beta_{ps} = 10^{\frac{\mathrm{PL}_{ps}}{10}} , \tag{2}$$

where, PL_{ps} is the path loss component, determined using the Floating-Intercept (FI) model [13], as shown below:

$$\mathrm{PL}^{\mathrm{FI}}(d)[\mathrm{dB}] = \alpha + 10.\beta \log_{10}(d) + X_{\sigma}^{\mathrm{FI}} \tag{3}$$

where, α represents the floating intercept in dB, β indicates the line slope and X_{σ}^{FI} symbolizes the large-scale signal variabilities as a function of the distance along the direct path.

2.2. Uplink data transmission

During the uplink data transmission phase, each sensor simultaneously transmits data to multiple APs using Binary Phase Shift Keying (BPSK) modulation. Each sensor is assigned a dedicated time slot to prevent multiple access interference from other sensors' signals. The received signals from multiple APs are combined at the CPU to exploit diversity gain, thereby enhancing the reliability and quality of the received signal and reducing the bit error rate (BER). Before transmitting data, the s^{th} sensor scales its symbol q_s, where $\mathbb{E}\left\{|q_s|^2\right\} = 1$, by a power control coefficient $\sqrt{\mu_s^u}$, satisfying $0 \le \mu_s^u \le 1$. According to digital modulation theory, this suggests that the sensor's transmission power level can be adjusted to improve transmission efficiency without compromising data integrity. The received signal at the p^{th} AP is represented by the following equation:

$$y_p^u = \sqrt{\mu_s^u} g_{ps} q_s + w_p^u \,. \tag{4}$$

In this expression w_p^u represents the noise vector at the p^{th} AP, which is assumed to follow a complex Gaussian distribution with zero mean and unit variance. Initially, all sensors are allocated the same power level, and the transmitted signal is normalized to have a power of 1. The average received power at the input of the receiver (at the p^{th} AP), after channel estimation, is the expected squared value of the MMSE estimate $\hat{g}_{ps}$ and is calculated as follows:

$$\gamma_{ps} \triangleq \mathbb{E}\left\{\left|\hat{g}_{ps}\right|^2\right\} = \frac{\beta_{ps}^2}{\beta_{ps}+1} \,. \tag{5}$$

The thermal noise power is expressed as:

$$noise\_power = B \times k_B \times T_0 \times noise\_figure \,, \tag{6}$$

Where B is the bandwidth (Hz), k_B is the Boltzmann constant, T_0 is the noise temperature, typically set at 290 Kelvin, and the noise figure represents the signal-to-noise ratio (SNR) degradation in the system. According to Shannon's formula [15], assuming that the bandwidth B is constant, the channel capacity of the s^{th} sensor under ideal conditions is described by the following expression:

$$C_s = B \times \log_2\left(1 + SNR \times N \times l_{tb}^2\right) = B \times \log_2\left(1 + \frac{\sum_{p=1}^{P} \gamma_{ps}}{noise\_power} \times \mathbb{E}(g_{ps})\right) \tag{7}$$

Where N is the number of receiving antennas. Since both the sensors and APs are equipped with a single antenna, $N=1$, l_{tb}^2 represents the mean value of the channel coefficients, specifically $l_{tb}^2 = \mathbb{E}(g_{ps})$.

The capacity of the weakest sensor is calculated using the following expression:

$$C_{weakest} = C_s \times P_{weakest} \tag{8}$$

Where $P_{weakest}$ is the transmit power of the weakest sensor. The average capacity of all sensors in the system (including S sensors) can be calculated using the arithmetic mean of the capacities of the sensors. Specifically:

$$C_{avg} = \frac{1}{S} \sum_{s=1}^{S} C_s \tag{9}$$

3. POWER CONTROL ALGORITHMS

3.1. Reasons for power control

When a sensor moves closer to an AP, its transmission power is reduced to conserve energy while maintaining adequate signal strength. Conversely, when the sensor moves farther away, its power is increased. However, if the sensor reaches its maximum power limit and continues to move further, the connection may be lost, and an OFF signal will be triggered. If the sensor carries critical data, a warning will alert the operator to prevent the machinery from moving too far. Power control is managed at the CPU, which can only detect signal degradation but cannot determine whether it is due to poor channel quality or reduced transmission power. Therefore, feedback from the sensor is necessary to inform the CPU of its current power level, helping to identify the cause of signal loss. Additional channel quality measurements, such as SNR, can also be performed at the AP to distinguish between channel degradation and power reduction. Intelligent power control algorithms are essential to optimize transmission power and interference resistance, ensuring the system adapts flexibly and efficiently to actual conditions.

3.2. Power control process

In the DMC IWSN model, the CPU monitors and adjusts the transmission power of the sensors according to the following procedure: The initial transmission power of each sensor is set between 1 mW and 5 mW to ensure efficient data transmission while conserving energy. During the uplink training phase, the APs receive pilot signals, signal strength and channel quality information from the sensors and forward this data to the CPU for processing. Based on the results, the CPU adjusts the power level of each sensor: if the channel quality is poor, the power is increased; if the channel quality is good, the power may be maintained or reduced to save energy and minimize interference. The CPU sends adjustment commands to the sensors via the APs during the downlink transmission phase, and the sensors implement these commands in the subsequent uplink transmission phase.

3.3. Max-Min power control algorithm

The MM power control algorithm [7] is designed to ensure that the "weakest" sensor (the sensor with the lowest capacity) can transmit data reliably. The objective of the MM algorithm in the uplink transmission scenario is to improve the capacity of the weakest sensor by adjusting the transmission power so that all sensors achieve the desired minimum capacity while adhering to power constraints. The transmission power of each sensor P_s ranges from 1 mW to 5 mW.This can be expressed through the following equation:

$$\begin{aligned} &\max_{\{\mu_s^u\}} \quad \min_{s=1,\ldots,S} C_s \\ &\text{subject to} \quad 0 \le \mu_s^u \le 1,\ s = 1,\ldots,S \\ &\qquad\qquad 1\,\text{mW} \le P_s \le 5\,\text{mW}. \end{aligned} \tag{10}$$

3.4. Window-Selection power control algorithm

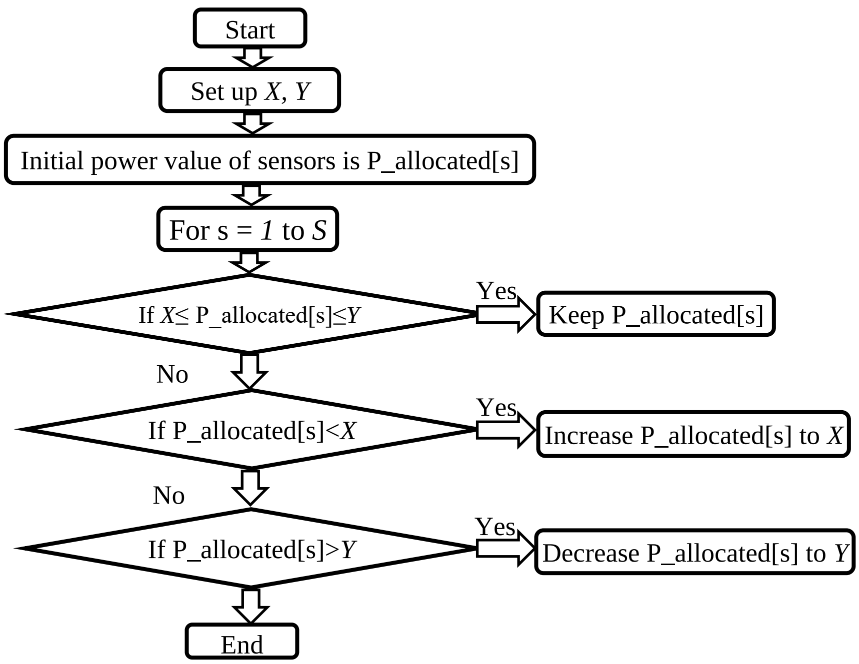

Figure 2. *Algorithm flowchart for Window Selection.*

To enhance flexibility and efficiency, this paper introduces the Window-Selection (WS) power control algorithm, which adjusts sensor power based on predefined thresholds to reduce interference, increase transmission efficiency, and improve reliability. WS adapts quickly to changes in production workshops by automatically adjusting sensor power according to real-time conditions. The algorithm functions as follows: it decreases power if it exceeds the upper limit, increases it if it falls below the lower limit, and keeps it unchanged if it is within the defined range. The WS algorithm flowchart is illustrated in figure 2.

The upper limit (70%-100% of maximum power) ensures strong signal strength, while the lower limit (10%-40%) minimizes interference and maintains connectivity. These thresholds are set based on signal quality, connection stability, and regulatory compliance. Qualitative evaluations suggest that WS is suitable for WSNs in production workshops due to its simplicity and ease of implementation. The WS algorithm is compared to the MM algorithm, as both aim to adjust power to maintain connection quality and minimize interference. While the MM algorithm focuses on optimizing the weakest sensor's capacity, WS uses predefined thresholds. Comparing WS and MM provides an objective benchmark to assess WS's efficiency and its potential improvements in practical scenarios. However, simulation results are needed for quantitative evaluation and precise comparison between the two algorithms. The specific implementation steps of the WS algorithm are as follows:

- ***Initialization:*** Determine the upper and lower power limits [X, Y].

- ***Power Adjustment:*** The algorithm iterates through each sensor to check the current power allocation. If the allocated power is within the acceptable range [X, Y], it remains unchanged. If the allocated power is lower than the minimum threshold X, it is increased to level X. If the allocated power is higher than the maximum threshold Y, it is reduced to level Y.

- ***Power Allocation:*** After processing all the sensors, the algorithm returns the adjusted power allocation, ensuring that all sensors have power levels within the permissible range.

4. RESULTS AND DISCUSSIONS

4.1. Input data

Table 1. *The settings of the simulation setup.*

Variable	Cost
Frequency (f) and Bandwidth (B)	4,5 GHz; 1 MHz
The number of AP (P) and the number of sensor (S)	2,3,4; 8,12,16
α, β, σ of LoS environment	41,45; 1,32; 1,79
α, β, σ of NLoS environment	16,22; 4,83; 3.91
Height of the AP mounted on the wall (Hp)	2,5 m
Height of the sensors mounted on the surface of the machinery (Hs)	from 0,5 m to 1,5 m
The dimensions of the production room (length × width × height)	10 m × 10 m × 3 m
Upper and lower power limits (X,Y)	40%, 70%

In the production workshop, there are K pieces of machinery, each equipped with several sensors on their surfaces, with a total of S sensors. The sensors transmit data directly to P APs, which are mounted on the walls at a height of 2,5 meters, while the sensors are positioned at heights ranging from 0,5 to 1,5 meters. The model utilizes a 1 MHz bandwidth, which is sufficient for short-range data transmission from the sensors, ensuring energy efficiency, reduced interference, and optimized performance within a 10 square meter room with a moderate number of sensors. The path loss coefficient is considered for both Line-of-Sight (LoS) and Non-Line-of-Sight (NloS) scenarios with predefined values. The room dimensions are 10m × 10m × 3m, representing a typical production workshop setup. The transmission power limits of the sensors are adjusted within a range of 40% to 70% to optimize performance and maintain stable connectivity. Detailed parameters are provided in table 1.

4.2. Simulation methods and tools

This paper uses Matlab to simulate and generate the Cumulative Distribution Functions (CDF) of the channel capacity for both the weakest sensor and the total capacity of all sensors during the uplink data transmission process. The use of CDF offers several significant advantages: it provides a comprehensive view of data distribution, enables system reliability assessment by measuring the probability of reaching specific threshold values, facilitates visual comparison between different power control methods, and offers detailed insights into system performance under various conditions. Additionally, Matlab's flexible simulation environment allows for easy parameter adjustments and testing across multiple scenarios.

4.3. Simulation results evaluation

First, quantitatively evaluate whether the proposed model using the TDMA technique performs better than the model without TDMA by examining a key quality metric: the average SNR. Figure 3a simulates the average SNR in the case where the number of sensors is fixed at S = 12 and the number of APs is varied at P = 2, 4, and 6. Figure 3b simulates the average SNR in the case where the number of APs is fixed at P = 3 and the number of sensors is varied at S = 8, 12, and 16. In both cases, whether changing the number of APs or the number of sensors, it is observed that the average SNR of the proposed DMC IWSN model consistently outperforms the average SNR of the model without using the technique. This demonstrates the superiority of the TDMA technique in eliminating multiple access interference between sensors, which significantly contributes to improving the average SNR.

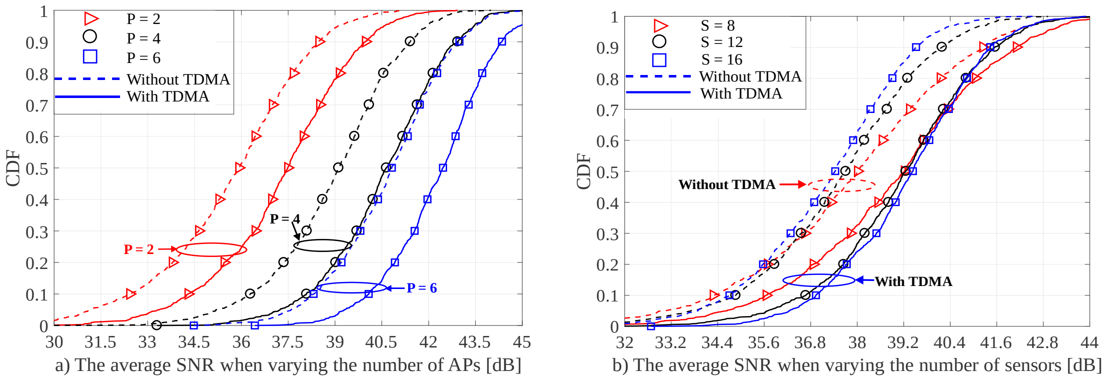

Figure 3. *Comparison of the average SNR of sensors in the DMC IWSN model using the TDMA technique with the model not using the TDMA technique.*

Subsequently, the paper investigates and evaluates the effectiveness of the WS algorithm in various cases. The simulation results compare the weakest sensor capacity and the average capacity of all sensors in the uplink data transmission of the DMC IWSN model under three scenarios: no power control, MM power control, and WS power control. In the figures, the WS algorithm is represented by a solid green line with square markers, the MM algorithm by a solid black line with circular markers, and no power control by a dashed red line with triangular markers. The DMC WSN model requires continuous and accurate data transmission to prevent production interruptions.

Low capacity of the “weakest” sensor can lead to data loss and latency, affecting monitoring and control processes. Enhancing the weakest sensor’s capacity is crucial for maintaining stable system operation. Figure 4a shows that, without power control, the weakest sensor’s capacity is at its lowest; the MM algorithm increases it to a moderate level, while the WS algorithm achieves the highest capacity, demonstrating superior performance. Figure 4b confirms that WS achieves the highest average capacity of all sensors, outperforming both MM and no power control scenarios.

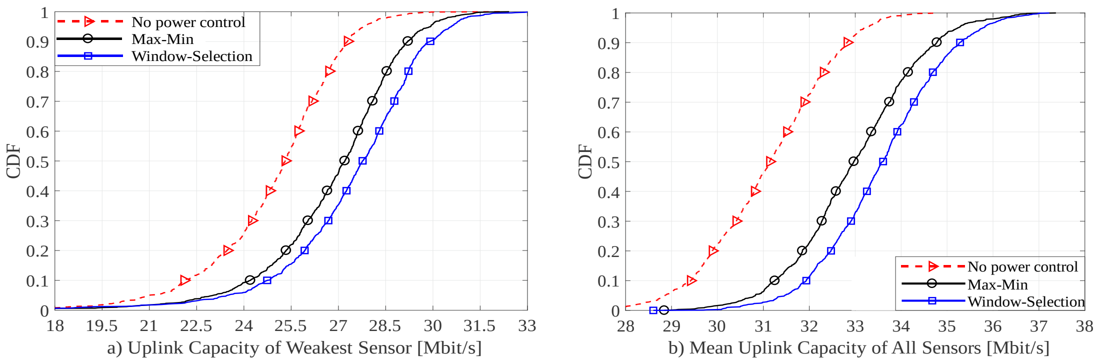

Figure 4. *Comparison of the weakest sensor capacity and the total capacity of all sensors when applying power control algorithms with P = 3 and S = 12.*

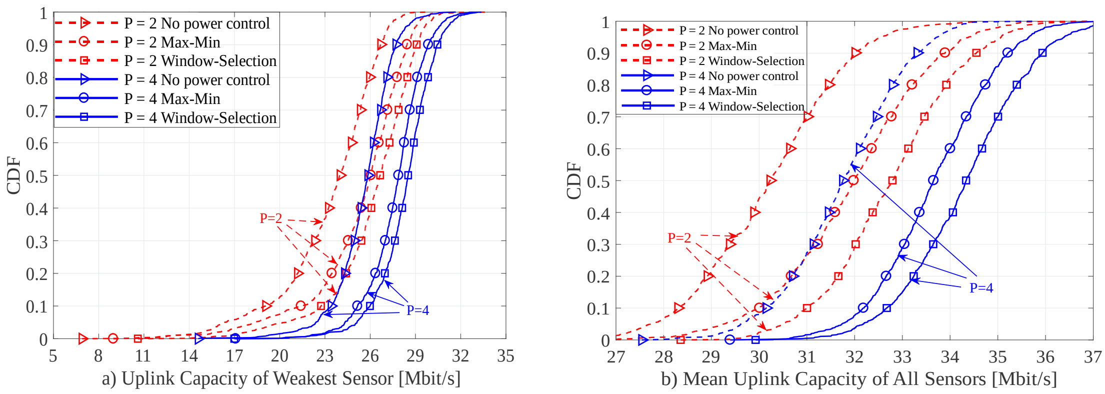

Figure 5. *Comparison of the weakest sensor capacity and the total capacity of all sensors when applying power control algorithms with varying numbers of APs and S = 12.*

Figures 5a and 5b show that when the number of APs increases from 2 to 4, sensor capacity is highest with the WS algorithm, moderate with the MM algorithm, and lowest without power control. As the number of APs increases, both the weakest sensor capacity and average capacity improve. This is due to enhanced spatial diversity, reduced interference, and better load balancing. More APs allow each sensor to connect to those with the best channel conditions, improving signal quality and capacity. Additionally, shorter distances to APs reduce interference and increase SNR. More APs also distribute the load more evenly, minimize errors, and enable more accurate channel estimation. As a result, increasing the number of APs significantly boosts both weakest sensor capacity and overall network capacity, ensuring stable connectivity and higher transmission efficiency.

Figures 6a and 6b show that with *S*=16, the WS power control algorithm achieves the highest sensor capacity, the MM algorithm reaches a moderate level, and without power control, capacity is at its lowest.

When *S*=8, WS and MM perform similarly due to lower interference, stable channels, and easier power adjustments, making it easier to reach optimal levels. As the number of sensors increases, resource sharing, interference, and power limits reduce the SNR of the weakest sensor, causing its capacity to decline. However, the average capacity of the system still increases because the network can better leverage data distribution, frequency efficiency, and resource allocation for sensors with good channel conditions. More sensors create a larger network with higher total capacity, enabling more data transmission compared to scenarios with fewer sensors.

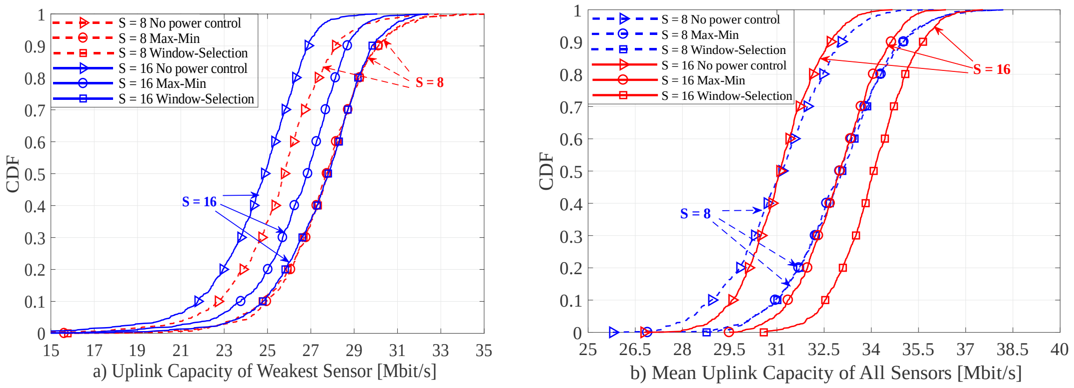

Figure 6. *Comparison of the weakest sensor capacity and the total capacity of all sensors when applying power control algorithms with varying numbers of sensors and P = 3.*

5. CONCLUSIONS

In this study, a DMC IWSN model was proposed for application in a factory production workshop. A new power control algorithm named WS was introduced, and the capacity of the weakest sensor and the total capacity of all sensors were compared when applying the two power control algorithms, WS and MM. The simulation results highlight the critical role of power control algorithms in enhancing sensor capacity in the DMC IWSN model. The results show that the sensor capacity in the DMC IWSN model, when applying the proposed WS algorithm, outperforms the MM algorithm and is significantly better than the scenario without power control, demonstrating the importance of WS in optimizing system performance. Future research will focus on expanding and applying the WS algorithm in various environments to assess its adaptability and effectiveness in more complex and dynamic scenarios. Additionally, further comparisons will be made between WS and other established power control algorithms to evaluate its relative performance. Finally, efforts will be directed towards optimizing and improving the WS algorithm to enhance energy efficiency, communication reliability, and overall system performance.

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TÓM TẮT

Phát triển thuật toán điều khiển công suất cho mạng cảm biến không dây công nghiệp đa kết nối động

Trong bài báo này, chúng tôi đề xuất một mô hình mạng cảm biến không dây công nghiệp đa kết nối động (DMC IWSN) nhằm nâng cao hiệu quả truyền dữ liệu trong xưởng sản xuất. Chúng tôi giới thiệu một thuật toán điều khiển công suất mới có tên là lựa chọn cửa sổ (WS), điều chỉnh công suất cảm biến dựa trên các giới hạn trên và dưới đã được xác định trước. Thuật toán này sẽ giảm công suất cảm biến khi vượt quá giới hạn trên, tăng công suất cảm biến khi thấp hơn giới hạn dưới và duy trì công suất cảm biến ổn định trong các giới hạn này. Chúng tôi so sánh hiệu suất của thuật toán WS, thuật toán Max-Min (MM) và trường hợp không điều khiển công suất dựa trên dung lượng của cảm biến yếu nhất và tổng dung lượng trong quá trình truyền dữ liệu đường lên. Kết quả mô phỏng cho thấy thuật toán WS đạt hiệu suất cao nhất, trong khi thuật toán MM cũng đạt hiệu quả trong việc cải thiện dung lượng cảm biến trong mô hình DMC IWSN.

Từ khoá: Mạng cảm biến không dây công nghiệp; Thuật toán điều khiển công suất; Lựa chọn cửa sổ; Thuật toán tối ưu hóa mức tối thiểu.