Int J Adv Manuf Technol (2013) 67:2377–2385
DOI 10.1007/s00170-012-4657-3

ORIGINAL ARTICLE

A protocol for processing interfered data in facility sensor networks

Wootae Jeong · Hoo Sang Ko · Heejong Lim · Shimon Y. Nof

Received: 11 May 2012 / Accepted: 21 November 2012 / Published online: 7 December 2012
© Springer-Verlag London 2012

Abstract Wireless sensor networks (WSNs) have recently extended application areas to numerous sectors such as industrial automation, military applications, transportation systems, building management, and environment surveillance. In particular, WSNs provide flexible, reliable, cost-effective solutions to monitor the real-time status of automated manufacturing facilities. A facility-specific WSN for reliable monitoring and efficient management of industrial facilities is called the facility sensor network (FSN). In general, industrial facilities run various electromagnetic devices causing electromagnetic interference (EMI), which disturbs wireless data communication. To obtain accurate and reliable data in such environments, the FSN needs to deal with the EMI by proper deployment of sensor nodes and their validation and fusion. This paper proposes a data processing protocol, called Interfered Sensor Data Processing Protocol (ISDPP) to handle the EMI affecting wireless communication. ISDPP is developed with a data fusion algorithm and an exponentially weighted moving average/fuzzy logic-based error detection method to obtain reliable information from the FSN. To evaluate the performance, experiments in various settings are performed in a test-bed manufacturing facility. The experimental results indicate the interfered data, and outliers can be filtered out even if unexpected interferences occur in the facility. The FSN with the ISDPP can provide efficient real-time monitoring solutions for various industrial applications.

Keywords Data fusion · Data processing protocol · Electromagnetic interference · Wireless sensor networks · Facility sensor networks

W. Jeong
Korea Railroad Research Institute, 360-1, Woram-dong, Uiwang, Gyeonggi-Do, Republic of Korea

H. S. Ko (✉)
Industrial and Manufacturing Engineering, Southern Illinois University Edwardsville, Edwardsville, IL 62026, USA
e-mail: hko@siue.edu

H. Lim
Krannert School of Management, Purdue University, 403 W State St, West Lafayette, IN 47907, USA

S. Y. Nof
School of Industrial Engineering, Purdue University, 315 N Grant St, West Lafayette, IN 47907, USA

1 Introduction

The facility sensor network (FSN) is an automation facility-specific wireless sensor network (WSN) developed as a reliable WSN solution for monitoring industrial facilities [1]. This emerging application of distributed WSN has been developed to enable reliable monitoring and efficient management in various automation applications. Manufacturing facility management, inventory management, and process control are just a few examples of FSN applications [2]. As it has been recognized in many research studies, WSNs using distributed sensors and actuators help reduce maintenance cost, increase the reliability, and provide flexibility and reconfigurability in manufacturing systems [3, 4]. Even though WSN applications are diverse and the characteristics of WSNs are application-specific, previous studies on WSNs have been primarily concerned with such issues as maximizing the lifetime of the network by minimizing energy consumption [5–7] and deploying sensor nodes so as to optimize network cost and quality of service [8–11]. The FSN research, however, primarily focuses on reliable monitoring functionality specifically to be useful for industrial facilities such as manufacturing systems, power plants, and hospitals. In these FSN applications, there exist site-specific interferences which disturb wireless data transmission. In real automation facility settings, there are many electrical and electromagnetic devices in use, which become electromagnetic emission sources and cause electromagnetic interference (EMI). For example, electrostatic discharge (ESD) events, parasitic emission from manufacturing equipment, and intentional emission from equipment using electromagnetic fields as a part of the process in manufacturing facilities can cause EMI which leads to sensor misreading [12]. This EMI interferes with the wireless communication among sensor nodes and the base station that collects the signal from the sensor nodes. As noticed in [1], the EMI from external emission sources existing in manufacturing facilities is the main cause of data distortion and performance degradation in wireless communications. In addition to EMI, the data transmission problem can be due to other reasons, e.g., signal attenuation, being out of the line of sight of visual sensors, and sensors being too proximate to one another. Even though this problem is supposed to be handled by the software and protocols provided by WSN manufacturers, it has been observed that incorrect readings still occur in the FSN due to the EMI [1]. Therefore, this article tackles the following research problem:

- In automation facilities, wireless data transmission is severely interfered with by electromagnetic emission sources or other types of disturbances that lead to incorrect data readings. How can the FSN provide reliable data for monitoring activities in such facilities?

To construct an effective facility monitoring system that is robust to EMI or other types of disturbances, this article presents a new data processing protocol. The protocol utilizes readings from redundant wireless sensor nodes deployed in a facility and functions at a higher layer than the routing protocols so as to concentrate on providing reliable data readings. This paper is organized as follows. Section 2 introduces the FSN research briefly and related research on interference in WSNs. The new data processing protocol, called Interfered Sensor Data Processing Protocol (ISDPP), is presented in Section 3. Section 4 describes the evaluation of the ISDPP in an FSN test-bed facility. Finally, Section 5 concludes this paper.

2 Facility sensor network

2.1 Facility sensor network description

The main goal of the FSN research is to effectively and efficiently deploy wireless sensor nodes for monitoring automation facilities with many electromagnetic emission sources, as illustrated in Fig. 1. Two specific objectives have been considered: (a) overcoming the effect of interference, which is the focus of this article, and (b) improving the efficiency of power consumption among distributed wireless sensor nodes [13]. The FSN has been developed and tested in the Manufacturing Center Model Factory, an automated manufacturing facility at Purdue University. The model factory is an integrated system of automated machine tools, robots, process control systems, and related equipment. There are six drop lines that can operate independently, or as a part of a larger integrated work cell, as depicted in Fig. 2. More detailed descriptions on the FSN test-bed facility can be found in [1].

Many studies on WSNs have shown wireless sensor nodes to function as intended for ideal or simulated environments. However, deploying wireless sensor nodes in real facilities raises various issues, including EMI, which result in reduced accuracy and reliability, and performance deterioration for the networked system. Applicability to such field environments must be studied before wireless sensor nodes are deployed at the targeted facilities.

There are a variety of potential FSN applications such as hazardous facilities monitoring, electricity or water infrastructural management systems, and remote manufacturing

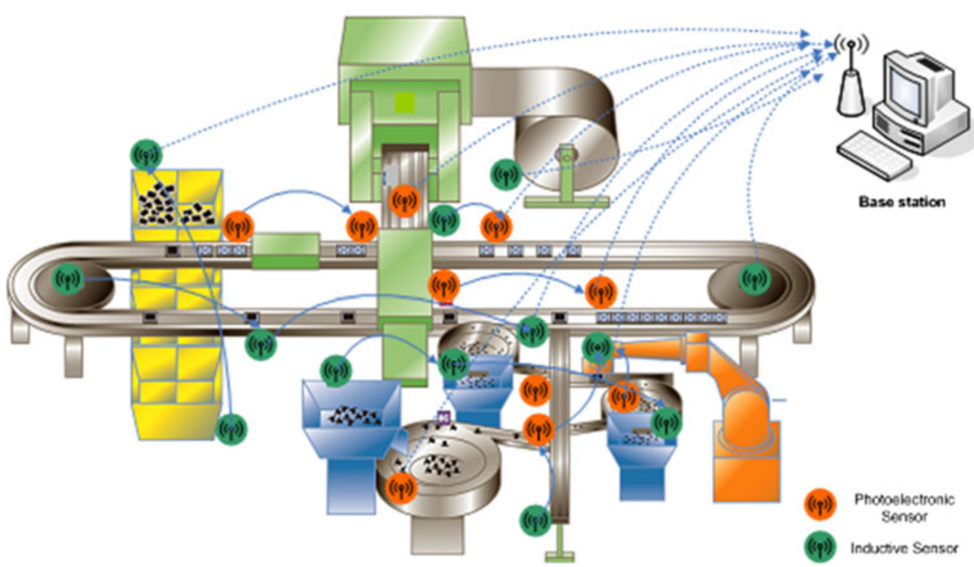

Fig. 1 FSN for monitoring automation systems

Fig. 2 An FSN test-bed facility

equipment certification. These applications require collecting and analyzing spatially and temporally dense data with minimal human intervention and thus real-time network processing capabilities. Besides, they also require network robustness, network reliability, and network configuration flexibility. Among these challenges, this study particularly focuses on obtaining accurate and reliable data from wireless sensor nodes deployed in the FSNs, which are affected by EMI in the noisy environments. This research tackles the EMI problem in the FSNs by means of an appropriate data processing protocol.

2.2 Backgrounds

The key issue in FSNs is to minimize the influence of EMI that distorts wireless communication. In general, it is assumed that the data at the transmitter are not exactly the same as those at the receiver due to EMI, which makes the received data inappropriate for monitoring purposes, i.e.,

$$D_{\mathrm{original}} \neq D_{\mathrm{received}} \quad (1)$$

where D is a set of data. Consequently, it is required to devise approaches to reducing the negative effect of interference.

The interference produced by electronic devices has long been studied. The impetus for the present research was the recognition of interference among wireless communication nodes. The basic principles of electrical noise and interference are well studied by [14]. Magnetic devices and local power transformers are the most complex and common source of interference. Materials connecting a site to the utility power supply can produce various interferences. For instance, the primary leads can act like transmission lines for high-frequency energy. Pulse-type noise can get in from ESD from various sources such as lightning or atmospherics, power-factor correction capacitors, or load switching. These pulses can get into the circuit over any conductor entering or leaving the circuit. In addition, radiated energy from radio frequency (RF) transmitters, television broadcasts, and radar sets can cause interference. Those signals may be detected or rectified during in-band communication [14]. Automation facilities consist of various machines and devices that radiate undesirable electromagnetic fields or conducted voltages and currents. In particular, there exist incidental radio frequency emitters with broadband interference in the automation facility. These include electric power transmission lines, electric motors, thermostats, bug zappers, etc. The effect and observation of noise and RF interference in manufacturing facilities are well addressed in detail by [15].

In an unreliable environment with many sources of EMI, use of redundant sensors can be a tentative solution to minimize uncertainties from biased data. The deployment of redundant sensors can bolster the fault tolerance of a system to sensor failure. Moreover, the system can deliver more accurate information to the user or to other systems by integrating multiple sensor readings. Current research on the signal-to-noise ratio and the signal-to-noise-plus-interference ratio has approached the issue of securing a clear signal under the environment where significant interferences are mixed. There are, however, some approaches that apply a combination of redundant sensors and data fusion schemes to process the multiple sensor readings. Data fusion techniques involve signal processing, statistics, numerical methods, pattern recognition, artificial intelligence, information theory, fuzzy logic, and neural networking [16].

The sensor validation and fusion approach applied in this research has been used in various fields. Sensor validation has been applied to guide automated vehicles in tracking and avoiding objects [17]. In order to preserve safety and reliability, a comprehensive methodology using AI and statistics has been developed. The method is effective for validating sensor readings, estimating the actual values despite faulty measurements, and detecting incipient sensor failures. It includes four logistic steps: redundancy creation, state prediction, sensor measurement validation and fusion, and fault detection through residue change detection. The advantage of this methodology is detecting multiple sensor failures, both abrupt and incipient. It can also detect subtle sensor failures like drifts in calibration and degradation of sensors.

A sophisticated theory and a model for information and sensor validation have also been developed by [18]. The model represents relationships among variables using Bayesian networks and makes use of probabilistic propagation to estimate the expected value of variables. Approaches for the detection of incorrect sensor representations were categorized as follows:

1. Hardware redundancy and majority voting: hardware is duplicated and votes to exclude outliers.
2. Analytical redundancy: mathematical and analytical models are required.
3. Temporal redundancy: statistical interpretation through repeated measurements.

Due to the natural imprecision of information decision making, fuzzy logic is used to integrate human expertise to estimate the confidence in sensor readings by using a membership function and fuzzy inference. Sensor value validation based on sensor redundancy has been developed for systems based on fault diagnosis knowledge by [19]. Systematic exploration of sensor redundancies has been proposed and used for quick validation for sensor values. This technique is based on causal relations and their interrelations within sensor redundancy graphs (SRGs). Any sensors in an SRG can potentially take advantage of any other sensors involved in the same SRG for validation. A validity level is defined and used to indicate the validation level of sensor values. The validation results provide information on system faults to the system's fault diagnosis knowledge-based system. A data fusion algorithm has been developed to provide a mechanism that extracts information from massively sensed data and identifies incipient sensor failures for a monitoring application [20].

In order to develop the methodology of sensor validation and fusion algorithms for the automation facility, this research has applied fuzzy logic-based approaches, called mote-fuzzy validation and fusion [20] and fuzzy sensor validation and fusion (FUSVAF) [21]. These approaches can determine the correlation among sensor data, assign a confidence value to each of them, and generate a fused weighted value. As a result, the ISDPP has been proposed in this paper.

3 ISDPP

For monitoring the automation facility where various interfering signals from electric and electromagnetic fields exist, a redundant sensor deployment strategy for the FSN has been proposed in our previous study [1]. Even with redundant sensors, however, radiated and conducted interferences can affect quality of data collected in the FSN. Therefore, it is essential to deal with the interference to assure accurate sensor data by a designated data processing protocol. The ISDPP proposed in this paper includes sensor data validation and fusion procedure to improve the reliability of signal data collected from multiple redundant sensors. The proposed ISDPP is also based on fuzzy logic to determine interference level or detecting errors in data sets. The novelty of this research is that it encompasses from sensor deployment, validation and fusion to error or interference detection to deal with the EMI caused by external sources in the FSN applications by means of the proposed ISDPP. The sequential steps of ISDPP are presented in Fig. 3. First, multiple sensors are redundantly deployed in the environment based on the strategy as explained in Section 3.1. Through ISDPP, the data from redundant sensors are collected at the base station, and the confidence level for each sensor reading is evaluated. Then, data fusion is applied to obtain representative values based on the confidence level of each sensor. Finally, the value at the next time step is predicted and compared to the actual value for error or interference detection. Each step is described in more detail in the subsequent sections.

3.1 Redundancy creation

First, the area of interest is divided into a number of square grid segments, in each of which sensor nodes are redundantly deployed. The number of sensors in each segment is determined by following the optimal deployment strategy to provide a higher level of redundancy to those areas highly affected by interference [1]:

$$\begin{aligned} \min \quad & \sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{j=1}^{J}\alpha^{n_{ij}}\frac{n_{ij}}{(x_i-x_k)^2+(y_i-y_k)^2} \\ \text{s.t.} \quad & \sum_{i=1}^{I}\sum_{j=1}^{J} n_{ij} \le \text{n} \\ & n_{ij} \ge 2 \end{aligned} \tag{2}$$

where (i, j) is the grid index on the 2-D space (i=1, 2,…, I; j=1, 2,…, J), k is the index of noise source (k=1, 2,…, K), α is the noise reduction parameter ($0<\alpha<1$), n_{ij} is the number of sensor nodes in segment (i, j), n is the total number of nodes, (x_i, y_i) is the center of segment (i, j), and (x_k, y_k) is the location of noise source k.

Even though the locations of sensor nodes are determined to reduce the influence of interference, data transmission is still disturbed by interference. This problem can be relieved by collecting data from redundant nodes. Fusing and validating data from redundant nodes reduce the possibility of faulty and biased readings [22]. To conduct experiments

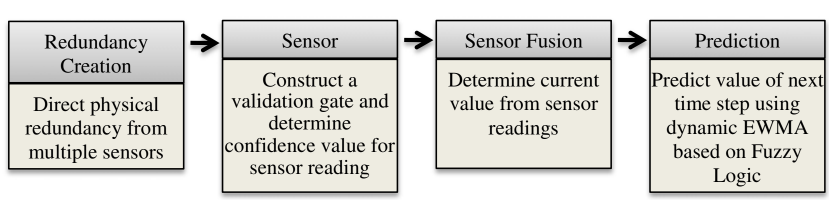

Fig. 3 Steps in the ISDPP

with multiple sensor readings, three wireless sensor nodes with identical thermal sensors have been redundantly deployed at the same location. Each sensor measures temperature of the same target device simultaneously. Redundantly measured values are reported to the base station for validation and fusion.

3.2 Sensor validation

Assuming that each sensor delivers an independent sensor reading, the sensor validation procedure evaluates the confidence level of measured values. The ISDPP estimates the correlation among various sensor readings. The correlation among incoming readings is used to generate a Gaussian curve for sensor validation. The correlation value denoted by $\widetilde{x}$ can be specified by using a median value approach that reveals a reasonable estimation of the majority of sensor readings. Once the correlation among sensor readings is calculated, the confidence value for each sensor reading is determined by a dynamic validation curve, which is based on the Gaussian curve generated from the specific sensor characteristics, the predicted value, and the correlation among incoming readings [20]. The confidence value from a particular sensor reading is defined as follows:

$$\sigma(z) = \begin{cases} 0 & z < v_{\text{left}} \\ \dfrac{e^{-\left(\frac{\widetilde{x}-z}{a_{\text{left}}}\right)^2} - e^{-\left(\frac{\widetilde{x}-v_{\text{left}}}{a_{\text{left}}}\right)^2}}{1-e^{-\left(\frac{\widetilde{x}-v_{\text{left}}}{a_{\text{left}}}\right)^2}} & v_{\text{left}} \le z < \widetilde{x} \\ \dfrac{e^{-\left(\frac{\widetilde{x}-z}{a_{\text{right}}}\right)^2} - e^{-\left(\frac{\widetilde{x}-v_{\text{right}}}{a_{\text{right}}}\right)^2}}{1-e^{-\left(\frac{\widetilde{x}-v_{\text{right}}}{a_{\text{right}}}\right)^2}} & \widetilde{x} \le z \le v_{\text{right}} \\ 0 & v_{\text{right}} < z \end{cases} \tag{3}$$

where $\sigma(z)$ is the confidence value corresponding to a particular sensor reading z; $\widetilde{x}$ is correlation among sensor readings; v_{left} and v_{right} are the left and right validation gate borders, respectively; and a_{left} and a_{right} are the tuning parameters for the left and right validation curves, which have been set to the same value as v_{left} and v_{right}, respectively, in the experiments.

If a sensor reading changes beyond the validation gate, the readings from the sensor are considered as outlier data affected by EMI or by sensor faults. In this research, v_{left} and v_{right} are determined statistically by a six-sigma approach. Mean and standard deviation are calculated from each sensor reading. Based on the evaluated values, six-sigma intervals, which cover 99.99966 % for each sensor, are constructed. Since all sensors have their own measurement deviation, each output interval cannot cover 99.99966 % of other sensor intervals. That is, an interval of the first sensor cannot be guaranteed to cover the same range of the sensor reading of the second sensor. Therefore, each sensor constructs its own output interval.

In the ISDPP, v_{right} is chosen as a maximum value among the upper limits of three intervals, and v_{left} is chosen as a minimum value among the lower limits. Assuming the effect of noise interference follows a normal distribution, the upper and lower limits for each sensor are determined by the six-sigma interval as follows:

$$\begin{aligned} L_i &= \mu_i - 3\sigma_i \\ U_i &= \mu_i + 3\sigma_i \end{aligned} \tag{4}$$

where i is the index of each sensor; L_i and U_i are the lower and the upper limit of the ith sensor's data, respectively; and μ_i and σ_i are the mean and the standard deviation of the ith sensor's data, respectively. Since these intervals cover most of the sensor data, the generated intervals can be used to determine the validation gate as follows:

$$\begin{aligned} v_{\text{left}} &= \min L_i \\ v_{\text{right}} &= \max U_i \end{aligned} \tag{5}$$

By using the estimates, the coverage rate of the sensor readings from multiple sensors can be calculated as follows:

$$\prod_{i=1}^{n} P\left(\frac{v_{\text{left}} - \mu_i}{\sigma_i / \sqrt{n_i}} < Z_i < \frac{v_{\text{right}} - \mu_i}{\sigma_i / \sqrt{n_i}}\right) \tag{6}$$

where n is the number of sensors, n_i is the number of the ith sensor's data, and Z_i represents the normalized ith sensor's data. Equation (6) assures the meaningful number of sensor readings included in the limit of Eq. (5). The data out of the range are considered as faulty data.

3.3 Sensor fusion and prediction

After the confidence value is calculated with the validation gate borders, the fused value can be obtained

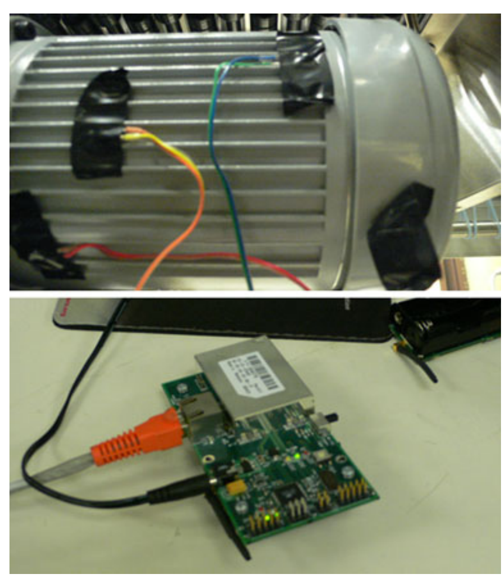

Fig. 4 Three thermal sensors (*top*) and the base station (*bottom*)

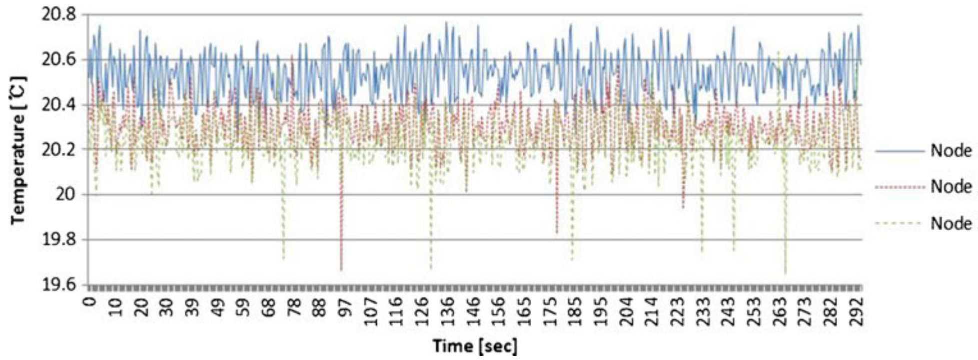

Fig. 5 Raw data collected inside the facility

based on the FUSVAF algorithm [21]. The fused value is given by

$$\widehat{x}_f = \frac{\sum_{i=1}^{n} z_i \sigma(z_i)}{\sum_{i=1}^{n} \sigma(z_i)} \tag{7}$$

where $\widehat{x}_f$ is the fused value, z_i is a measurement from the ith sensor, and $\sigma(z_i)$ is the confidence value of z_i.

Based on the fused value $\widehat{x}_f$, a value for the next time step can be predicted. An exponentially weighted moving average (EWMA) predictor is used to construct an adaptive time series data set. The EWMA assumes that the "good" historical data are representative of the in-control process. Since the ISDPP uses past data as a basis to decide how severely the current data have been interfered with, the ISDPP can satisfy the assumption of the EWMA. The EWMA also offers the best trade-off between responsiveness, smoothness, and stability. In the ISDPP, the EWMA is applied as follows:

$$\widehat{x}(k+1) = \alpha\widehat{x}(k) + (1-\alpha)\widehat{x}_f(k) \tag{8}$$

where $\widehat{x}(k)$ is the predicted value at time k, $\widehat{x}_f(k)$ is the fused value at time k, and α is the parameter to adapt the prediction.

The predicted value decides whether interference is severe or any critical error is detected in the next time step. Once the predicted is determined, it is compared with the new fused value generated at the next time step. Based on the comparison, the level of EMI can be determined or errors in the data set (i.e., significant deviations from the predicted values) can be detected. In the EWMA prediction procedure, α is the adaptive parameter carried by noise. If the system is transient, α is set to a small value so as to reduce the lag induced by the history. On the other hand, if the system is steady, α is set to a value large enough to weigh the history more, as the variation in measurements is very likely caused by interference at the instant. Ideally, α must be adaptive to the system status; however, it is not feasible to build an exact model of α since it may require too much computing power to run the protocol in real time. Therefore, a fuzzy logic is adopted in the ISDPP to implement the rules to set the value of α. To adjust the value of α dynamically according to the system state, a max–min Mamdani fuzzy inference method is developed with triangular membership functions and the following rule set:

1. If *change of readings* is small, then set α large, e.g., α=0.8.
2. If change of readings is medium, then set α medium, e.g., α=0.5.
3. If change of readings is large, then set α small, e.g., α=0.2.

4 Performance evaluation of the ISDPP

As described in Section 1, there exist various electric and inducted interferences in automation facilities. To evaluate its performance, the ISDPP has been implemented and applied to the data set collected from the FSN test-bed facility with many sources of EMI. Three redundant thermal sensor nodes report the temperature change of an induction motor in the facility. Each sensor is wired to a wireless sensor node (MDA320 data acquisition board attached to MICAz mote,

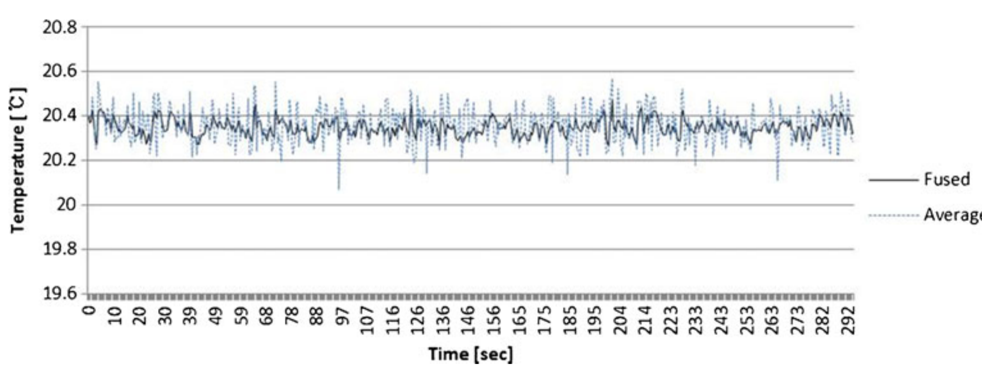

Fig. 6 Data inside the facility processed by ISDPP

Table 1 Comparison of variances of data sets collected in the test-bed facility

Source	Sensor 1	Sensor 2	Sensor 3	ISDPP
Variance	0.0318	0.0366	0.0468	0.0058
p value from F test with processed data	<0.001	<0.001	<0.001	–

manufactured by Crossbow) as shown in Fig. 4. The three wireless sensor nodes transmit collected data to the base station (MIB600).

The ISDPP evaluates the measurements from the redundant nodes by scoring their confidence levels. After the evaluation, the ISDPP estimates the actual measurement by fusing the three sensor data according to their corresponding validation scores. The fused value is recorded as the current temperature and also used to forecast the expected value for the next period. The overall procedure is repeated in real time.

Figure 5 shows the sensor data streams from the three temperature sensor nodes attached at the motor housing. Each sensor is calibrated and measures temperature of the motor running at a constant speed. The mean and variance of the motor temperature are independently recorded from the three nodes. Since the temperature is measured from the same motor that has run at a constant speed for a sufficient period of time, the readings must be almost constant. Figure 5, however, shows unexpected peaks and fluctuations caused by noise and EMI. Figure 6 shows the data fused by the ISDPP along with the average values. The high peaks and severe fluctuations and biases are significantly reduced by ISDPP, while the average values still show high variability since all three nodes are affected by EMI. These results imply that the negative influence of interference can be alleviated, and reliable values can be achieved by the ISDPP.

The implication can be also confirmed by variance analysis. Variance of received data can be used as an indicator of interference based on the following noise model [1]:

$$y = x + e \tag{9}$$

where y is the data received by BS; x is the actual data measured by a sensor; and e is the error caused by interference. Then,

$$\mathrm{Var(y)} = \mathrm{Var(e)} \tag{10}$$

Proof $\mathrm{Var(y)} = \mathrm{Var(x+e)} = \mathrm{Var(x)} + \mathrm{Var(e)} + \mathrm{Cov(x,e)} = \mathrm{Var(e)}$ assuming $\mathrm{Cov}(x, e)\approx 0$, and $\mathrm{Var}(x)=0$ when the temperature is constant.

The variance analysis results shown in Table 1 indicate that the data processed by ISDPP yield a significantly lower variance than the individual sensor data set, which means the influence of interference has been significantly reduced.

In addition, the performance of the ISDPP protocol has been tested in a less noisy setting. Instead of a complex automation facility where many noise and EMI sources exist, the wireless sensor nodes are installed and tested at a separate hallway of the facility without any equipment. The fluctuation has significantly lessened due to the reduced noise sources; however, readings from the three sensor nodes still indicate some influence of interference, as shown in Fig. 7. Figure 8 shows the result after the ISDPP is applied compared to the average values. The peaks and fluctuation are significantly reduced by ISDPP. The averages in this case work better than the ones in the previous experiment, but still result in higher variability.

The variance analysis is also conducted with the data set collected from the hallway setting. The ISDPP yields significant improvements as shown in the F test results in Table 2. As recognized in both settings, the proposed ISDPP provides more reliable information for end users to make decisions about the status of the automation facility. This protocol has been tested in the test-bed facility but can be extended to other applications, where redundant sensor nodes are required to deal with EMI by validating and consolidating measured data streams.

The experimental data sampled in Fig. 5 show the analog signals from sensor nodes affected by not only EMI but also noise; however, the high peaks and large variability in Fig. 5 are mainly caused by interference, as noticed in our previous

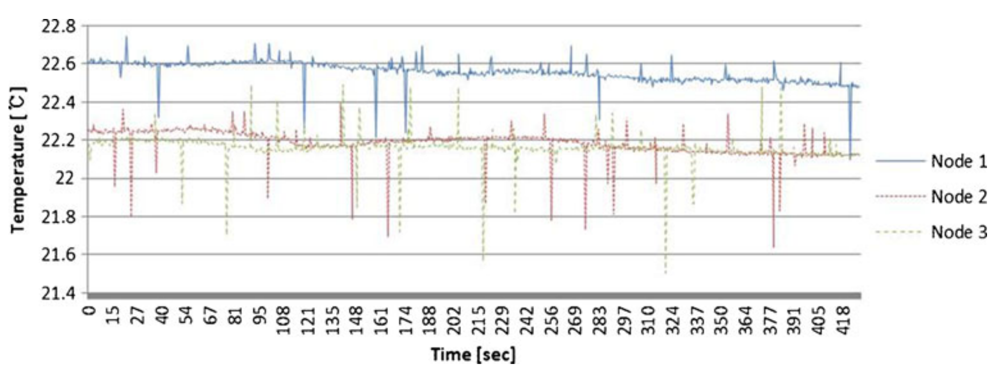

Fig. 7 Raw data collected outside the facility

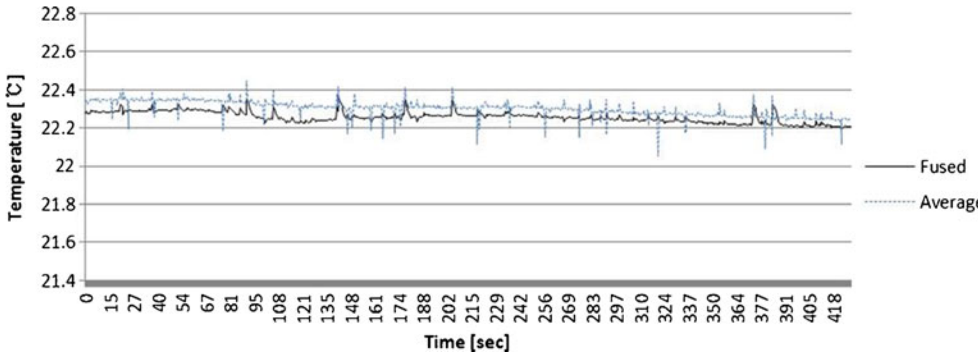

Fig. 8 Data outside the facility processed by ISDPP

work [1]. The main purpose of the ISDPP is the robustness of collected data without traditional noise filters even in the interfered environment. The processed data depicted in Fig. 6 are obtained only by using the ISDPP without traditional noise- or interference-removing filters. In addition, the experimental results depicted in Figs. 7 and 8 indicate the ISDPP works well in the less noisy yet still interfered environment.

5 Conclusion

This article proposed an approach to reliable real-time facility monitoring by WSNs. By applying the proposed ISDPP to the FSN, combined with the sensor deployment strategy, wireless data transmission can be robust against noise and EMI. Although the EMI from electromagnetic devices is the main source of interference in this research, the protocol can also deal with any inevitable disturbances existing in the facility. Depending on applications, some traditional noise reduction techniques such as low- or high-pass filters may work better than the ISDPP. However, those filters require a system noise identification procedure including noise frequency domain. The great advantage of the proposed ISDPP is that it can simplify the application procedure. Even without knowing noise or interference frequency domain, the protocol can yield good data processing performance and provide reliable information in severely interfered environments. In addition, the ISDPP can supplement the data correction feature in the routing protocol provided by WSN manufacturers. The routing protocols are supposed to provide the correction feature, but it turns out this feature is not reliable enough. On top of the routing protocols, the ISDPP functions at a higher layer to make wireless communication even more reliable. Besides, the fuzzy logic applied to the protocol makes the parameters adjustable to the level of interference in the facilities.

Table 2 Comparison of variances of data sets collected outside the test-bed facility

Source	Sensor 1	Sensor 2	Sensor 3	ISDPP
Variance	0.0087	0.0145	0.0120	0.0025
p value from F test with processed data	<0.001	<0.001	<0.001	–

The deployment strategy and the proposed ISDPP would facilitate the use of WSNs to monitor facilities that contain various electromagnetic devices or other types of interference sources. For example, the FSN can be applied to monitor healthcare facilities where spatially and temporally massive data sets should be continuously collected and monitored in an extremely reliable way. Moreover, a decision support system for critical error detection and resolution can be built upon a real-time architecture based on the FSN with the ISDPP. Since the ISDPP has been developed to work in real time, the protocol can be directly embedded into the gateway at the hardware level or in the wireless node management system at the software level.

The FSN with the ISDPP can be applied and extended to various real-time automation problems. Currently, a study is being conducted on FSN-based certification of remote manufacturing equipment. Manufacturing equipment must be validated and certified on a regular basis to meet certain process specifications. The validation process includes collecting and monitoring physical properties at critical locations on the equipment. The current test procedure is cumbersome and time consuming since (1) it is a labor-intensive job; (2) it is usually performed with wired sensors, which may collide with physical constraints in the facility; and (3) the location is often hazardous and unreachable. The FSN can be deployed to decrease setup time, eliminate the need to route wires into the equipment, and avoid any dangerous situations, while providing wireless monitoring capability using the ISDPP.

In the future, optimization rules to determine efficient redundancy level will be further investigated. Besides, only three sampling nodes have been used in the test-bed experiments, but more sensor nodes should be deployed to facilities in greater scale. In addition, a proper procedure to adjust the parameters, used in the sensor validation and prediction, will be studied before the protocol can be brought online. Ultimately, the FSN will integrate application/facility-specific event detection and resolution capability by mining the data collected through ISDPP.

Acknowledgments This study was partially supported by PRISM Center at Purdue University, Center for Advanced Manufacturing in Purdue Discovery Park, Naval Surface Warfare Center Crane Division, Eli Lilly, Emerson, and the Ministry of Environment in Korea (Eco-Innovation, No. E211-40002-0003-0).

References

1. Ko HS, Lim H, Jeong W, Nof SY (2010) A statistical analysis of interference and effective deployment strategies for facility-specific wireless sensor networks. Comput Ind 61(5):472–479
2. Akyildiz IF, Su W, Sankarasubramaniam Y, Cayirci E (2002) A survey on sensor networks. IEEE Commun Mag 40(8):102–105
3. Chong CY, Kumar SP (2003) Sensor networks: evolution, opportunities, and challenges. Proc IEEE 91(8):1247–1256
4. Abrishambaf R, Hashemipour M, Bal M (2012) Structural modeling of industrial wireless sensor and actuator networks for reconfigurable mechatronic systems. Int J Adv Manuf Technol. doi:10.1007/s00170-012-4070-y
5. Cheng ST, Hsu CL (2005) Genetic optimal deployment in wireless sensor networks. J Internet Technol 6(1):9–18
6. Jeong W, Nof SY (2009) A collaborative sensor network middleware for automated production systems. Comput Ind Eng 57(1):106–113
7. Tang F, You I, Guo S, Guo M, Ma Y (2010) A chain-cluster based routing algorithm for wireless sensor networks. J Intell Manuf. doi:10.1007/s10845-010-0413-4
8. Xu K, Wang Q, Hassanein H, Takahara G (2005) Optimal wireless sensor networks (WSNs) deployment: minimum cost with lifetime constraint. In: Proceedings of the IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob’05), Montreal, QC, Canada
9. Chin TL, Ramanathan P, Saluja KK (2006) Optimal sensor distribution for maximum exposure in a region with obstacles. In: Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM’06), San Francisco, CA, USA
10. Hou YT, Lee TC, Jeng BC, Chen CM (2006) Optimal coverage deployment for wireless sensor networks. In: Proceedings of the 8th International Conference of Advanced Communication Technology, Phoenix Park, South Korea
11. Toumpis S, Tassiulas L (2006) Optimal deployment of large wireless sensor networks. IEEE Trans Inf Theory 52(7):2935–2953
12. Kraz V (2007) EMI issues in the manufacturing environment. Conformity 12(1):38–42
13. Jeong W, Nof SY (2008) Performance evaluation of wireless sensor network protocols for industrial applications. J Intell Manuf 19(3):335–345
14. Morrison R (1991) Noise and other interfering signals. Wiley, New York
15. Krishnamurthy L, Adler R, Buonadonna P, Chhabra J, Flanigan M, Kushalnagar N, Nachman L, Yarvis M (2005) Design and deployment of industrial sensor networks: experiences from a semiconductor plant and the North Sea. In: Proceedings of the 3rd International Conference on Embedded Networked Sensor Systems (SenSys’05), San Diego, CA, USA
16. Prajitno P, Mort N (2001) A fuzzy model-based multi-sensor data fusion system. In: Proceedings of SPIE—sensor fusion: architectures, algorithms, and applications V 4385:301–312, Orlando, FL, USA
17. Alag S, Goebel K, Agogino A (1995) Methodology for intelligent sensor validation and fusion used in tracking and avoidance of objects for automated vehicles. In: Proceedings of the American Control Conference, Seattle, WA, USA
18. Ibarguengoytia PH, Vadera S, Sucar LE (2006) A probabilistic model for information and sensor validation. Comput J 49(1):113–126
19. Lee SC (1994) Sensor value validation based on systematic exploration of the sensor redundancy for fault diagnosis KBS. IEEE Trans Syst Man Cybern 24(4):594–605
20. Wen YJ, Agogino A, Goebel K (2004) Fuzzy validation and fusion for wireless sensor networks. In: Proceedings of the ASME International Mechanical Engineering Congress and Exposition, Anaheim, CA, USA
21. Goebel K, Agogino A (1999) Fuzzy sensor fusion for gas turbine power plants. In: Proceedings of SPIE—sensor fusion: architectures, algorithms, and applications III 3719:52–61, Orlando, FL, USA
22. Solberg AHS, Jain AK, Taxt T (1994) Multisource classification of remotely sensed data: fusion of Landsat TM and SAR images. IEEE Trans Geosci Remote Sens 32(4):768–778