Intelligent Sensing for Internet of Things Systems

Li-Ling Hung*
Computer Science and Information Engineering, Aletheia University, Taiwan
llhung@au.edu.tw

Abstract

The Internet of things (IoT) has been used for many applications. These applications are accomplished by numerous sensors that detect and share information. When people use the detected information in an IoT system to improve the performance of services, also called the intelligence of the system, this type of IoT is named artificial intelligence of things. This paper proposes a model for improving the flexibility of sensors to enhance the intelligence of IoT. The model defines the quality levels of events and monitoring data for all types of monitoring. In the model, the data or events with different levels have different transmission priority. To reduce energy consumption of detection and transmission, the detecting period of sensors can be set to be longer when the monitored status is normal. In the model application, the sensors shorten the event detection and reaction times. Therefore, the efficiency of monitoring is enhanced. The evaluation demonstrates that the event detection and response times of the proposed mechanism are better than those of other mechanisms.

Keywords: Internet of things, IoT, Artificial intelligence of things, AIoT, Intelligent sensing

1 Introduction

Internet of things (IoT) systems have been applied in various domains, such as smart cities, industry, agriculture, health care, as well as transportation [1-6]. In an IoT application system, sensors, software, and technologies form an interconnected network to exchange information to achieve the system's purpose. Active sensing and efficient sharing are two key concerns in IoT systems [7].

Studies have proposed that the continual enhancement of the IoT service is the attractive feature of an IoT system [7]. An IoT system with the ability to learn is called the artificial intelligence of things (AIoT). In recent years, IoT systems integrating the artificial intelligence (AI) technology into AIoT systems have become popular [13]. The large quantity of data collected from IoT systems provide opportunities to learn from those systems [12]. For example, as Figure 1 depicts, an AIoT system collects information from IoT devices and then analyzes the information in the learning and decision-making subsystem. After learning, the subsystem may relay the learning result back to improve the intelligence and service of IoT systems.

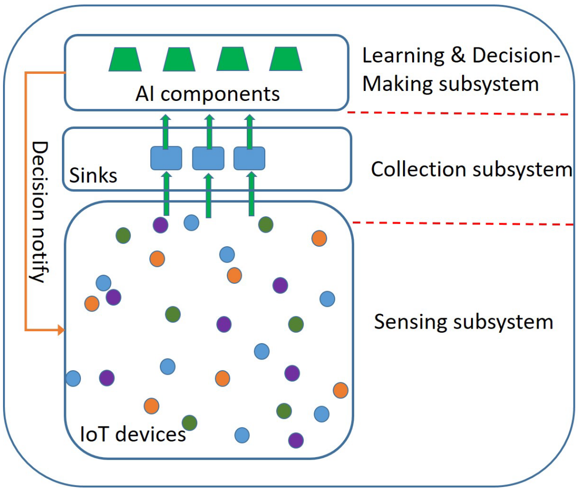

Figure 1. AIoT system architecture

To improve the intelligence of IoT systems, detection efficiency is a pivotal concern. According to the design of sensors, the detection is only active periodically to maintain energy efficiency. A longer detection period of sensors may save energy in detection but sacrifice detection efficiency because sensors reflect the detection results after longer periods and event notification occurs more slowly compared with a shorter detection period. In general, events do not occur suddenly; they follow a sequence of changing processes. This type of event can be monitored and have its progress halted before becoming too serious when a potential indicator of a trend toward an event is identified. Furthermore, some factors that are monitored by different sensors may be signs of a more serious event. Therefore, careful monitoring of the indicators of events or serious events can improve the detection efficiency.

Quality of service (QoS) is usually used to represent the qualities of transmission latency or event response time [3, 6]. A higher QoS associated with a packet or message implies that the data should be transmitted with shorter latency and shorter response time. In this study's proposed system, we employ QoS to represent the quality of transmission latency for detected data. The potential factors of events and potential factors signifying serious events have higher QoS because they should be monitored more carefully.

In our IoT application system, the types of sensors and monitoring events are varied. We propose defining QoS for factors in different types of events and classifying the QoS of detected factors according to the values and types of factors. Data with different QoS ratings may be packed and sent with different waiting times.

The main contributions of this paper are as follows:

*Corresponding Author: Li-Ling Hung; E-mail: llhung@au.edu.tw
DOI: 10.53106/160792642022012301019

- We propose sensors that adjust themselves according to detected situations.
- We propose self-adjusting sensors to conform with sensing requirements from other sensors or systems.
- We design a flexible model of sensors to increase the intelligence of IoT applications efficiently.
- The proposed sensors can improve the development of AIoT because the sensors may apply the results of AI algorithms easily and flexibly.

2 Related Studies

Research on IoT systems has paid considerable attention to meeting the requirements of detection efficiency and transmission efficiency [7-11]. Singh *et al.* [8-9] proposed cluster-based mechanism to reduce the number of transmissions; because fewer transmissions occur, the number of transmission collisions decrease and the performance of transmissions is improved. Hung [10] proposed a mechanism whereby transmissions of sensors are arranged according their sensor groups and the time; following the defined rules, the transmissions in the environment can be progress parallel and collision free. In practice, cooperative transmissions are required in an IoT system. Hammi *et al.* [1] demonstrated that multiple heterogeneous IoT system cooperating transmissions are a requirement of the IoT platform. Hung [11] proposed a cooperative routing mechanism to facilitate transmissions for heterogeneous sensors. Khalifa *et al.* [14] integrated heterogeneous technologies to improve communication performance. We propose exploiting the property of heterogeneous transmissions in the IoT to adjust the sensor for greater monitoring efficiency.

In terms of detection, AI-Turjman and Alturjman [15] proposed a smart sensing framework to address the privacy and quality of detection data. Hung [11] proposed a sensory mechanism to improve the accuracy of event detection. In addition, the sensing elements and parameters can be modified during synchronization. Lin *et al.* [5, 16-17] designed a series of smart Arduino systems for application in agriculture or smart campuses. The intelligence of Arduino is developed according to the system platform. Moreover, these devices collect information continuously to improve their intelligence. However, sensor adjustment in these platforms is performed by users. If the sensors were able to self-adjust, real-time adjustment would rapidly improve the efficiency of sensor detections. To detect events more efficiently, we propose the use of sensors that adjust themselves according to detected messages.

Chweya *et al.* [12] suggested that the incorporation of a learning subsystem into an IoT system improves the intelligence of the system. Users adjust the sensors or implement new sensors according to the learning results. In terms of adaption, the sensors adjust themselves to satisfy the result of the learning system or adjust themselves by detected information that would be more flexible and more intelligent for a given IoT system.

Zhou *et al.* [19] proposed IoT devices with learning abilities. Each device can calculate based on collected data. Such devices reduce the transmission load because they transmit the result only. However, deploying devices with learning ability is expensive. In our design, the sensors are vigilantly observed for variations in detected data. When detected data signifies an abnormal or ominous situation, the sensor adjusts its actions of detection and transmission.

Distinguishing services according to the QoS of events can improve the efficiency for key ones. Agarkhed *et al.* [6, 11, 18] proposed routing protocols for QoS-aware monitoring environments. Those protocols dispatch transmissions according to their QoS values, thereby improving the performance in an energy-efficient manner. Focusing on things with different activities and rated at different QoSs is helpful in event transmission and detection.

The purpose of this paper is to detail an IoT system architecture aimed at improving monitoring efficiency through enhancing the ability and flexibility of sensors. To notify the system (and users) of crucial events sooner, events with higher QoS ratings are transmitted first. Furthermore, to detect events sooner, data with higher QoS ratings prompt the sensors to detect related elements more frequently. To improve flexibility, the sensors can adjust themselves to satisfy the QoS of detected data. The values of data that occur close to some events imply that those events may occur soon; thus, such data has a higher monitoring priority. Therefore, the sensors in such systems expose and notify events more efficiently than those in systems where sensors require manual adjustment do.

3 Architecture of Proposed Mechanism

In this paper, the construction of an action model for an intelligent sensing for IoT systems (ISIT) mechanism is proposed. For ease of presentation, a monitored item, such as temperature, humidity, or brightness, is considered an element, and the detected value of an element is considered a parameter in this paper. The model defines the QoS levels of elements and corresponding actions for the parameters. The actions include the frequencies of detections and transmissions for the status levels of sensors. Each sensor detects elements and transmits parameters according to its QoS status. In addition, a sensor may adjust its QoS status when its current status does not satisfy the levels of the parameter detected by itself or received from related sensors. In this paper, the current status represents the current QoS level of a sensor if not stated.

The events in the IoT system can be classified into simple and complex ones. A simple event is caused by one abnormal element; a complex event is caused by two or more abnormal elements that are detected by one sensor or different sensors. Sometimes, a simple sensor detects and monitors only a single element. In practice, a sensor may detect two or more elements at the same time. Either the simple sensor or complex sensor can apply the model in which each element having its own QoS level, and the current status of the sensor is adjusted to satisfy the highest level in its parameters.

The proposed mechanism and the actions of a sensor using the ISIT in an IoT system are depicted in Figure 2. A sensor sets the QoS model when it initiates or receives a modifying request; subsection 3.1 describes the content of the model. For energy efficiency, sensors detect the elements periodically. The action “idle” is interrupted by the sensor’s timer or by neighbors’ messages. The details of actions performed after the idling process is interrupted are described in subsection 3.3.

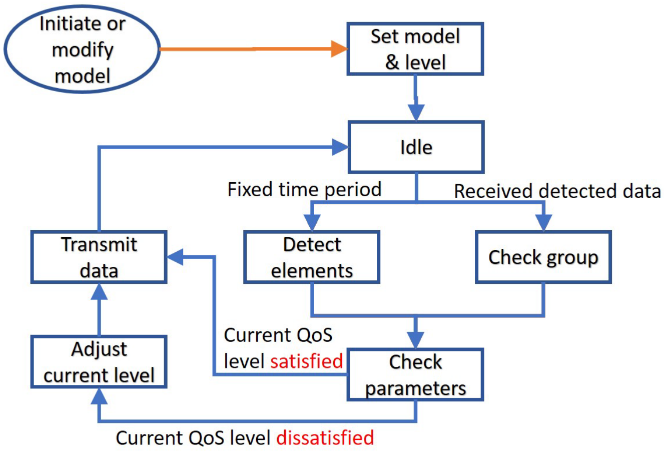

Figure 2. Sensor actions

3.1 QoS Models of Sensors

The QoS model of each sensor defines the QoS levels for its related elements, including the parameter range and the corresponding actions of the sensor. In addition, the groups of related elements that may cause complex events are included. In the QoS model, each element has different QoS levels and each level has its corresponding range of values and actions for sensors. The actions define the frequencies of detections and transmissions for the QoS levels of each element. A higher QoS level indicates that the parameter has a shorter detection period and a higher transmission priority; that is, the sensor will detect its parameters more frequently and transmit the record sooner when the QoS level is higher.

For instance, Table 1 displays the QoS model defined in sensor s_i. Sensor s_i is responsible for detecting elements e_b and e_c. The elements e_a and e_d are not detected by s_i but are related to s_i because the values of e_a and e_b may represent the status of an event. The model anticipates that elements e_a and e_b may form an event when their values are in the range of level 3. If the detected parameter of e_b is in the range (b_1, b_2), the QoS of this parameter is level 2. When a received parameter of e_a is in the range (a_2, a_3), on level 3, from its neighbors, the current status of s_i is adjusted to level 3 to monitor the event caused by abnormal e_a and e_b values.

Table 1. QoS model in sensor s_i. Under "QoS level", a larger number represents a higher QoS level

Element	Range	QoS level	Action(times/s)		Event group
			Detec.	Trans.	
e_a	(a_2,a_3)	3	25	20	e_b
e_b	(b_1,b_2)	2	15	15	
e_b	(b_2,b_3)	3	25	20	e_a
e_b	(b_3,b_4)	4	35	35	e_a, e_d
e_c	(c_1,c_2)	2	15	15	
e_c	(c_2,c_3)	3	25	20	e_d
e_d	(d_1,d_2)	3	25	20	e_c
e_d	(d_3,d_4)	4	35	35	e_b, e_c

Except initialization, the IoT application system can modify the QoS model by a modification request. The request can be sent when an IoT application synchronizes the system or resets the system periodically.

3.2 Groups of Sensors and Groups of Events

As noted previously in this section, some complex events are caused by two or more elements that are detected by different sensors. These sensors are usually neighbors. In these events, the neighboring sensors must monitor these elements simultaneously. Therefore, the neighboring sensors are regarded as the same sensor groups. The sensors will examine the parameters of these events when they receive data detected by their neighbors in the same sensor group.

Furthermore, to improve the efficiency of monitoring complex events, the related elements for an event are regarded as being in the same event group in a sensor model for integrated monitoring. For example, elements e_a and e_b in Table 1 are treated as being in the same event group. When a sensor receives a data packet from its sensor group having a parameter that is not detected by this sensor but is listed in event group of the model, the status of this sensor may be upgraded to a higher level of event monitoring as required even though the sensor does not detect the element itself. When an element causes two or more complex events, the element is included in those event groups. For instance, in Table 1, elements e_a and e_b cause a complex event when the parameters are in level 3, and elements e_b and e_d cause another complex event when the parameters are in level 4. Thus, the event group fields of the first and last rows include e_b.

The event group of an element is defined in the QoS model of a sensor, but the sensor group is not. Because an event arises only from elements that must be bound in the neighboring section, sensors examine event groups only when the received packet is transmitted by a sensor in the same sensor group.

3.3 Actions of Sensors

At the time of initialization, sensors in the IoT system set the levels of parameters in their QoS models and their current QoS statuses. After being initialized, sensors in the IoT system detect the elements periodically and transmit the detection information according to the current status and definitions in the model. A sensor may adjust its QoS status when the current status does not satisfy the QoS levels of monitored elements. To reduce complexity and energy consumption, each sensor maintains a current QoS status and the element with the highest QoS level.

Sensors determine their statuses according to their own QoS models and the data detected or received, and they do not notify their statuses or modifications to neighbors. Two occasions in which the current status for a sensor is adjusted are for detected data and for received data. The adjustment for detected data is driven by the sensor itself and is described in the forthcoming subsection 3.3.1; the adjustment for received data is driven by neighboring sensors in the same group and is described in subsection 3.3.2.

3.3.1 Adjustment for detected data

When a sensor detects its parameters, it examines the current status and the levels of parameters from the model. If one of the parameters is in the range of a higher QoS level than its current status, the current status is increased to satisfy the parameter with the highest level and the parameter with highest level is recorded. By contrast, if all the parameters are located in the range of lower QoS levels than current status, including the parameter recorded as the highest level one, the current status decreases to satisfy the highest level of these parameters. If the recorded parameter with the highest level is not detected, the current status is not modified; this prevents QoS level conflicts between the detected parameters and the other monitored parameters. After the current status is modified, the next detection time of the sensor is adjusted. This adjustment is driven by the detection of a sensor.

3.3.2 Adjustment for received data

When sensor s_i receives a packet p_j from other sensor s_o, sensor s_i examines its sensor group. If s_i and s_o are in the same sensor group, s_i compares the parameters in p_j with its QoS model. If a parameter is found in p_j and the model and the level of this parameter is higher than the current status, s_i increases its current status to satisfy the higher QoS level as required and records the parameter as the highest QoS level. In addition, the actions of s_i are modified according to the model defined. If all the levels of related parameters are lower than the current QoS status and the recorded parameter with highest QoS is an element in p_j, s_i decreases the current status to satisfy the highest level of related elements and records the parameter with the highest QoS level. In other words, if receiving one parameter from the sensor in the same group, the sensor confirms that the current status satisfies the parameter QoS level. If not, the level of the current QoS is modified to satisfy the highest level requirement. The adjustment is driven by the reception of a sensor.

4 Evaluation and Discussion

This section evaluates the performance of proposed ISIT and two smart sensing schemes named SSRM [10] and AAIT [19]. SSRM proposed a smart sensing and routing mechanism to monitor varied environment efficiently and adjust sensors' parameters at synchronizing periodically. AAIT proposed the mechanism that raises the computation of sensors to reduce the load of transmissions. The sensors in AAIT form a multi-layer network IoT system. After calculating and learning by themselves, the sensors transmit calculated result only instead of many raw data. The sensors designed in AAIT are not adjustable. In order to improve the intelligence of AAIT, we alter AAIT to a new mechanism that sensors are able to adjust its parameters, named AAIT2. Sensors in AAIT2 adjust themselves when they receive requests from others, for instance, the decision subsystem in Figure 1. For ease of presentation, AAITs represents AAIT and AAIT2 if not stated.

In the view of qualitative analysis. Except AAIT, the other three mechanisms employ adjustable sensors. Sensors in SSRM or AAIT2 adjust themselves according to modifying requests from a decision subsystem which learns from received data and makes decisions; sensors in ISIT adjust themselves according to their QoS model and the model can be modified by requests from decision subsystem. In model ISIT, the activities of sensors for different QoSs are defined. Those activities include the lengths of detection period and transmission period. Following the ISIT design, sensors sense more frequently when they sense something abnormal which shows signs of events or errors. Therefore, sensors can notice and detect events rapidly. Because sensors in AAIT2 or SSRM adjust themselves according to requests from the decision subsystem that makes decisions after receiving related event notifications, the sensors adjust their parameters slower than those in ISIT do. Because the sensors in AAITs need to calculate a set of neural network, the cost of each sensor in AAITs is costlier than the sensors in other mechanism. The mentioned characteristics of mechanisms are summarized as Table 2.

Table 2. Characteristics of mechanisms in qualitative analysis

Characteristic	AAIT	AAIT2	SSRM	ISIT
Adjustable sensors	×	✓	✓	✓
Sensor driven adjusted	×	×	×	✓
Request driven Adjusted	×	✓	✓	✓
Activities for varied QoSs	×	×	×	✓
Detection adjustment	None	slow	slow	rapid
Cost of each sensor	costly	costly	fair	fair

In order to evaluate the performance of mechanisms in quantitative analysis, we simulate the mechanism in varied situations. The parameters of simulations are list in Table 3. Because AAIT does not change its detection period, we set the frequency of detection is 30 times per second for efficient detection. The other mechanisms are adjustable, the initial detection frequency is less for energy efficiency and the frequency will be increased if necessary.

Table 3. Simulation parameters

Parameter	Value
Size of network field	300m x 300m
Frequency of detection	15-45 times/sec
Number of element types	6-10
Number of event types	6-15
Number of sensor group types	4-7
Energy consumed for detection	40nJ/bit
Energy consumed for transmission	50nJ/bit
Event occurrence ratio	5% - 40%

We evaluate these mechanisms on event detected time, event reported time, and event reacted time which are shown in Figure 3 to Figure 5. Figure 3 shows the average event detected time of mechanisms. The event detected time of an event is the period between the time it occurs and the time it is detected. Because events are detected when sensors detect actively, the average event detected time of a mechanism depends on the length of detection period and the sensitivity of period modification. In ISIT, sensors increase the detection frequency directly when they detect or receive abnormal statuses of monitored elements. Therefore, the detection time of sensors in ISIT decreases when the event ratio increases. In SSRM and AAIT2, the adjustments of sensors are not driven by themselves. The detection frequency may be modified when they receive the modification request from decision subsystem at synchronizing. Thus, before the next synchronizing, the lengths of detection period for SSRM and AAIT2 are similar even through the ratio of event occurrence increase. Hence, as shown in Figure 3, the fluctuations of average detected time for AAIT2 and SSRM are similar. In addition, those event detected time is longer than that using ISIT. Furthermore, using AAIT2, the event detection is indirect because sensors detect the status of elements and realize the events after a number of computing. In addition, when ratio of event occurrence increase, AAIT2 need more time than SSRM to detect event when the detection frequency of them are the same. On the other hand, although AAIT has higher frequency of detection initially, because the higher event ratio increases the computations that will decrease the detection ability of AAIT, when the ratio of event occurrence is more than 15%, the time for event detection is more than ISIT.

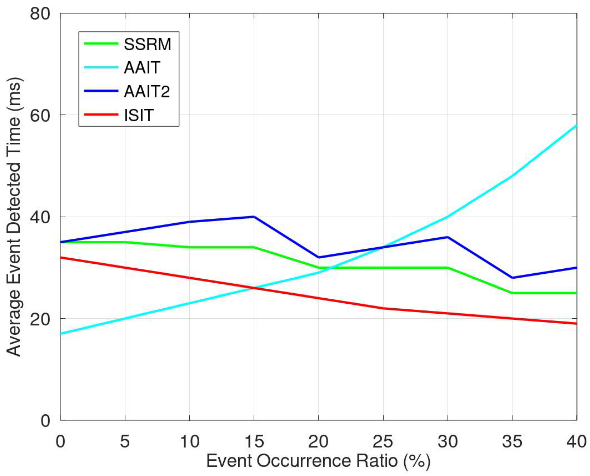

Figure 3. The average event detected time of mechanisms in different event occurrence ratios

Figure 4 shows the event reported time of mechanisms. The event reported time is the period for an event between the time it occurs and the time it is notified to decision subsystem. The event reported time of mechanisms are influenced by their detection and transmission schemes. Considering transmission collision, the packets in smaller size are transmitted more efficiently than those in larger size. Because mechanisms AAITs, include AAIT and AAIT2, transmit the results only, the size of each transmitted packet of AAITs is smaller. Thus, when increasing the event occurrence, the event reported time of AAITs does not increase obviously. In addition, AAIT detects events more frequently than AAIT2 initially. Because the detection period of AAIT is shorter than that of AAIT2, the reported time of AAIT is less than AAIT2. However, the detected time of AAIT2 becomes shorter than that of AAIT when the event occurrence ratio is more than 22%. Thus, AAIT2 reports events faster than AAIT as shown in Figure 4. On the other hand, because the loads of transmissions in SSRM and ISIT is heavier when the event ratio increased, the average event reported time increased also. Therefore, the event reported time of ISIT and SSRM is much longer than AAITs. In other words, the simulation shows that the transmission schemes result in the difference between two groups and the detection schemes result in the difference in those groups.

Figure 5 depicts the event reacted time of mechanisms. The event reacted time is the period for an event between the time it occurs and the time related sensors adjust for it. The sensors in ISIT adjust the detection frequency themselves when they detect the parameters which belong to higher QoS level. Thus, the event react time of them is short as depicted in Figure 5. On the other hand, the sensors in AAIT2 and SSRM are adjusted when they receive the requests from decision subsystem after it receives the notifications. Therefore, the sensors reacted time of AAIT2 and SSRM is much longer. Although AAIT has higher frequency of detection and has shorter event detected time, the sensors in AAIT are not able to adjust. Thus, the event reacted time of AAIT does not show in Figure 5.

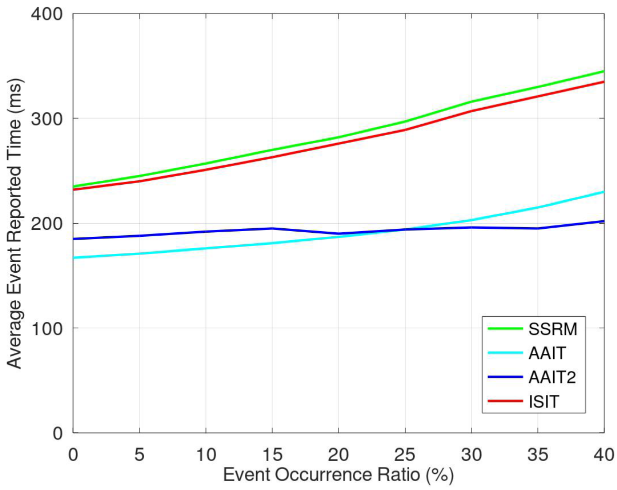

Figure 4. The event reported time of mechanisms in different event occurrence ratios

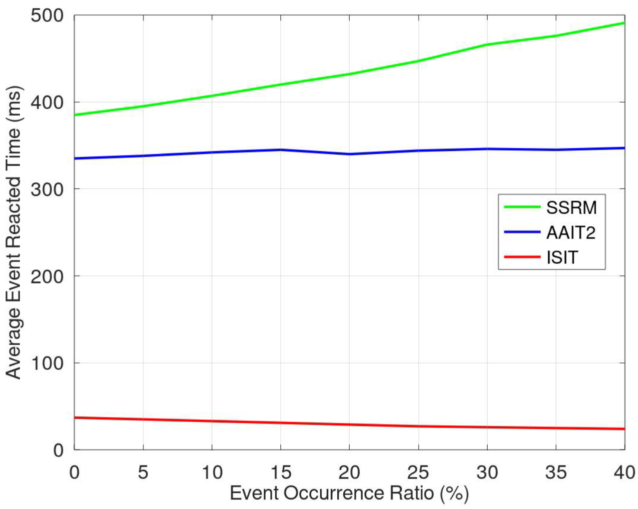

Figure 5. The event reacted time of mechanisms in different event occurrence ratios

Furthermore, Figure 6 shows the energy consumption of mechanisms. The solid lines represent the result when the events are formed in gradual progress. For actions of sensors, each transmission consumes more energy than each detection. In addition, each detection consumes more energy than each computation. According to the increasing of event occurrence, the energy consumption increase rapidly because the number of transmission increased. Because the number of transmissions for AAIT is the most, the energy consumed for AAIT is the most. The numbers of transmission for the other three mechanisms are similar, but each transmission for AAIT2 consumes less energy than that for ISIT or SSRM because the transmission size in AAIT2 is the least. On the other hand, the dotted lines show the result when the events are formed in varied situations. The adjustments driven by sensors are only for related sensors in ISIT. Moreover, the adjustments driven by decision subsystem are for entire sensors. Hence, the energy consumption of ISIT increase less than that of others when event occurrence increases because the sensors without missions do not consume energy for busy detections. Therefore, the proposed mechanism is good not only when the events are formed in gradual progress, but also when the events formed in varied situations because the sensors raise or lower their QoS level according their and neighbors' detection results rapidly.

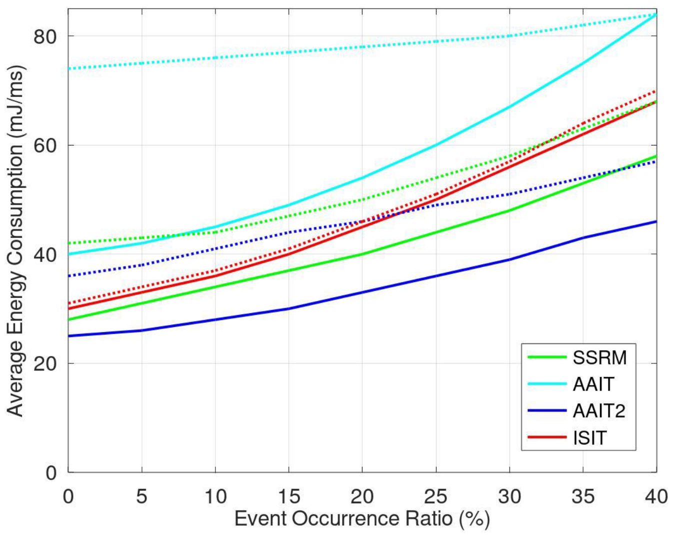

Figure 6. The energy consumption of mechanisms in different event occurrence ratios

Summarize the evaluations, the event detected time and event reacted time of sensors in ISIT are more excellent than other mechanisms because of the adjustable detection design of sensors. Because ISIT does not pay attentions on transmissions, the reported time of ISIT is more than AAITs. However, the energy efficiency of ISIT is better than SSRM and AAIT when event occurrence ratio increases. Because each sensor in ISIT is in the appropriate detection and transmission situations itself.

5 Conclusion and Future Work

This paper details the development of a protocol for self-adjusting sensors to satisfy diverse and complex situations. Each sensor has the intelligence to adjust itself following its QoS model, and the model defines different activities for different levels. Because sensors in the proposed mechanism adjust themselves immediately when abnormal situations are detected, the reaction time of the proposed protocol is excellent. Moreover, the detection frequency is higher when a sensor detects a worsening scenario. Thus, the event detection of the proposed mechanism outperforms those of other systems. Upon applying the protocol, the self-adjusting sensors shorten event detection and notification times. Therefore, the efficiency of monitoring is enhanced. Future research should include implementations of varied adjustable sensors to simulate practical application in relevant systems.

6 Acknowledgments

This work was supported in part by the Ministry of Science in Taiwan under contracts MOST 109-2221-E-156-002.

References

[1] B. Hammi, R. Khatoun, S. Zeadally, A. Fayad, L. Khoukhi, IoT technologies for smart cities, *IET Networks*, Vol. 7, No. 1, pp. 1-13, January, 2018.

[2] K. Li, T. Zhou, B. Liu, Internet-based intelligent and sustainable manufacturing: developments and challenges, *The International Journal of Advanced Manufacturing Technology*, Vol. 108, No. 5-6, pp. 1767-1791, May, 2020.

[3] L. Anifah, M. R. Rahmadian, R. Firmansyah, M. S. Zuhrie, Industrial Monitoring and Controlling System on Pressure Machines Using Internet of Thing (IoT), *International Conference on Science and Technology*, Surabaya, Indonesia, 2019, pp. 17-18.

[4] J. Mocnej, A. Pekar, W. K. G. Seah, P. Papcun, E. Kajati, D. Cupkova, J. Koziorek, I. Zolotova, Quality-enabled decentralized IoT architecture with efficient resources utilization, *Robotics and Computer-Integrated Manufacturing*, Vol. 67, Article No. 102001, February, 2021.

[5] W.-L. Chen, Y.-B. Lin, F.-L. Ng, C. U. Liu, Y.-W. Lin, RiceTalk: Rice Blast Detection Using Internet of Things and Artificial Intelligence Technologies, *IEEE Internet of Things Journal*, Vol. 7, No. 2, pp. 1001-1010, February, 2020.

[6] A. H. Sodhro, M. S. Obaidat, Q. H. Abbasi, P. Pace, S. Pirbhulal, A. Yasar, G. Fortino, M. A. Imran, M. Qaraqe, Quality of Service Optimization in an IoT-Driven Intelligent Transportation System, *IEEE Wireless Communications*, Vol. 26, No. 6, pp. 10-17, December, 2019.

[7] F. A. Awin, Y. M. Alginahi, E. Abdel-Raheem, K. Tepe, Technical issues on cognitive radio-based Internet of Things systems: A survey, *IEEE Access*, Vol. 7, pp. 97887-97908, July, 2019.

[8] I. Y. Mohammed, A. G. A. Elrahim, Energy Efficient Routing Protocol for Heterogeneous Wireless Sensor Networks, *SUST Journal of Engineering and Computer Science*, Vol. 20, No. 1, pp. 1-10, 2019.

[9] S. Singh, A. Malik, R. Kumar, Energy efficient heterogeneous DEEC protocol for enhancing lifetime in WSNs, *International Journal Engineering Science and Technology*, Vol. 20, No. 1, pp. 345-353, February, 2017.

[10] L.-L. Hung, A Smart Sensing and Routing Mechanism for Wireless Sensor Networks, *MDPI Sensors*, Vol. 20, No. 19, Article No. 5720, October, 2020

[11] L.-L. Hung, F.-Y. Leu, K.-L. Tsai, C.-Y. Ko, Energy-Efficient Cooperative Routing Scheme for Heterogeneous Wireless Sensor Networks, *IEEE Access*, Vol. 8, pp. 56321-56332, March, 2020.

[12] R. Chweya, S.-S. M. Ajubade, A. K. Buba, M. Samuel, IoT and Big Data Technologies: Opportunities and Challenges for Higher Learning, *International Journal of Recent Technology and Engineering*, Vol. 9, No. 2, pp. 909-913, July, 2020.

[13] J. P. Lemayian, F. Al-Turjman, Intelligent IoT Communication in Smart Environments: An Overview, in: F. Al-Turjman (Eds.), *Artifical Intelligence in IoT*, Springer, 2019, pp. 207-221.

[14] T. Khalifa, A. Abdrabou, K. Shaban, A. M. Gaouda, Heterogeneous Wireless Networks for Smart Grid Distribution Systems: Advantages and Limitations, *MDPI Sensor*, Vol. 18, No. 5, Article No. 1517, May, 2018.

[15] F. Al-Turjman, S. Alturjman, Confidential smart-sensing framework in the IoT era, *The Journal of Supercomputing*, Vol. 74, No. 10, pp. 5187-5198, October, 2018.

[16] Y.-W. Lin, Y.-B. Lin, M.-T. Yang, J.-H. Lin, ArduTalk: An Arduino Network Application Development Platform Based on IoTtalk, *IEEE Systems Journal*, Vol. 13, No. 1, pp. 468-476, March, 2019.

[17] Y.-B. Lin, M.-Z. Shieh, Y.-W. Lin, DormTalk: edge computing for the dormitory applications on campus, *IET Networks*, Vol. 8, No. 3, pp. 179-186, May, 2019.

[18] J. Agarkhed, P. Y. Dattatraya, S. R. Patil, Performance Evaluation of QoS-Aware Routing Protocols in Wireless Sensor Networks, in: S. C. Satapathy, V. K. Prasad, B. P. Rani, S. K. Udgata, K. S. Raju (Eds.), *International Conference on Computational Intelligence and Informatics*, Vol. 507, Springer, 2016, pp. 559-569.

[19] J. Zhou, Y. Wang, K. Ota, M. Dong, AAIoT: Accelerating Artificial Intelligence in IoT Systems, *IEEE Wireless Communications Letters*, Vol. 8, No. 3, pp. 825-828, June, 2019.

Biography

Li-Ling Hung received the Ph.D. degree in computer science and information engineering from the National Taiwan University of Science and Technology, Taipei, Taiwan, in 2008. She is currently an Associate Professor with the Departent of Computer Science and Information Engineering, Aletheia University, Taipei, Taiwan. Her research interests include vehicular ad hoc networks, wireless sensor networks, underwater wireless sensor networks, ad hoc wireless networks, the Internet of Things, machine learning, and cyber physical systems.