Lightweight Fault-Detection Scheme for Solar Insecticidal Lamp IoTs

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The Solar Insecticidal Lamp Internet of Things (SIL-IoTs) is an emerging paradigm that extends Internet of Things (IoT) technology to agricultural-enabled electronic devices. Ensuring the dependability and safety of SIL-IoTs is crucial for pest monitoring, prediction, and prevention.

Keywords: distributed fault detection ; solar insecticidal lamps internet of things

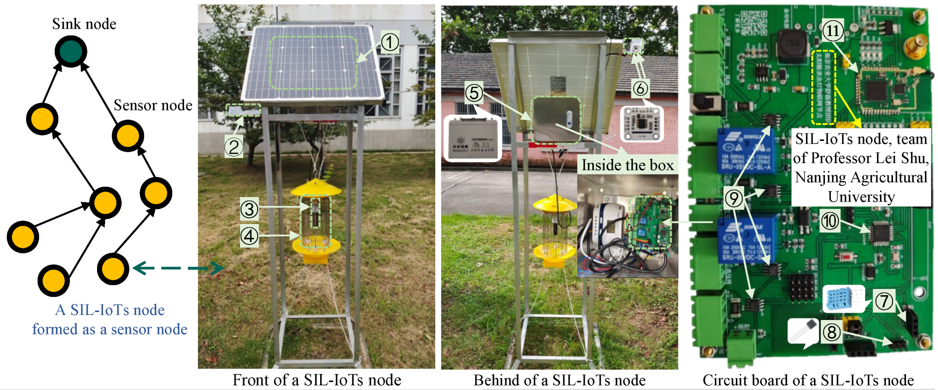
1. Introduction

The solar insecticidal lamp (SIL) has gained widespread adoption in agricultural pest management and control, offering an environmentally friendly approach to pest control. Recent advancements in IoT technology have enabled SILs to expand their functionalities and improve operational life through pest monitoring, pest outbreak area positioning, and energy optimization in battery-powered devices [1]. Yang et al. [2] have indicated that the fixed effective killing distance of SIL ranges from 50 to 110 m, which falls within the communication range of ZigBee. Leveraging this characteristic, SIL-IoTs nodes can collect and transmit data related to pest statistics (e.g., the number of pests killed in a short period of time), component status information (e.g., voltage and current values of various components), and meteorological environment information to the back-end system via the network [3]. This data transmission allows farmers to accurately use pesticides in areas with varying pest populations, therefore avoiding excessive pesticide usage, as shown in **Table 1**. Moreover, IoT devices facilitate continuous and remote monitoring of SIL-IoTs' component status, enabling timely failure reporting and improving the reliability and data quality of SIL-IoTs.

Table 1. Comparison of SIL and SIL-IoTs node.

	SIL	SIL-IoTs
Price	**CNY 1100 (about $160)**	**CNY 1500 (about $219)**
Function	**Harvest energy** **Kill pest**	**SIL's functions** **Count killed pests** **Monitor component status** **Monitor environment**
Advantage	**Cheap** **Easy to use**	**Provide farmers with killed pest statistics for targeted pesticide usage** **Detect faults timely to ensure reliability of SIL-IoTs**
Drawback	**Inability to perceive information**	**Expensive price**

Figure 1 illustrates some key elements and functionalities of a typical SIL-IoTs node. Among other core components, sensors are used to further embed various intelligence capabilities into the SIL-IoTs node. For example, a solar energy system allows the SIL-IoTs node to be charged during the day, while at night it is programmed to automatically attract pests. A metal mesh is used to kill pests (by contact) by discharging a sudden high-voltage pulse. During this process, several intelligent sensors monitor environmental conditions, calculate the number of pests killed and determine the operating status of the modules. During rainy periods, the SIL-IoTs switch to sleep mode by turning off the lure lamp and metal mesh to prevent damage and save energy.



SIL

	Module	Detail
①	Solar panel	Harvest energy at day
②	Rain fall detector	Turn off SIL if it rains to protect SIL
③	Lure lamp	Attract pest at night
④	Metal mesh	Release high voltage pulse to kill pest at night
⑤	Battery	Store energy

IoTs

	Module	Detail
⑥	Light intensity sensor	Information perception of crop growth environment
⑦	Air temperature sensor	
⑧	Box temperature sensor	Monitor thermal State of battery
⑨	Voltage & current sensor	Monitor ①, ③, ④ and ⑤
⑩	Arduino	Control command
⑪	ZigBee	Transmit data

Figure 1. An example of a SIL-IoTs node, where a temperature sensor inside an electrical box is used to monitor the thermal state of the battery and IoTs devices. The light intensity sensor is used to monitor the condition of solar panels. More details can be seen from [4].

Typically, SIL-IoTs nodes are geographically dispersed and deployed in an unattended and harsh environment. Inevitably, the SIL-IoTs nodes are susceptible to aging, theft, and vandalism [5]. According to several relevant literature [6], there have been 19 related news reports of SIL failures in the past 20 years, and a total of more than 7000 SILs have been abandoned due to insufficient fault detection and maintenance work, which is not conducive to the promotion of products and the establishment of user confidence.

The above issues result in faulty conditions and abnormal operation of SIL-IoTs nodes, which affect the operational capabilities and overall performance of SIL-IoTs. For instance, if the energy harvesting system fails (causing the solar panel to continuously charge the battery without a control mechanism), the battery will eventually heat up and cause performance degradation, or even explode and cause damage to SIL-IoTs nodes. In addition, the deployment of SIL-IoTs nodes in remote locations makes real-time inspection and maintenance difficult. Therefore, it is a challenging task (to monitor and detect the SIL-IoTs node faults) to ensure adequate and efficient operation throughout the lifecycle. If there is an adequate provision of computational capacity and energy, traditional approaches can provide good detection performance in terms of real-time response, data loss prevention, and less data transmission [7][8].

2. A Lightweight Fault-Detection Scheme for Resource-Constrained Solar Insecticidal Lamp IoTs

Fault detection and prediction are critical to enabling proactive intelligent device health management [9][10]. A well-established approach is to detect faults in a centralized manner at the server level, which requires periodic collection of information from all nodes (i.e., each SIL-IoTs periodically transmits to the data collection server) and performing inference processes at the back end [7]. For instance, the connectivity metrics of all the nodes are transmitted to the back end and the root causes are troubleshot using a decision tree [11]. Tang et al. [12] proposed a neighborhood hidden conditional random field method to monitor the health of wireless sensor networks. The posterior probability of different faulty states is estimated and used to classify faults at the back end.

As shown in **Table 2**, unlike established and traditional IoT applications, SIL-IoTs devices are mainly characterized by (1) limited on-board storage and computing capacity, (2) remote deployment locations with poor network conditions, and (3) deployment to cover a large geographical area. Due to the high communication overhead and detection delay caused by multi-hop data transmission, this approach is not efficient in terms of both overall detection performance and resource allocation (i.e., devices are battery-powered and therefore have limited energy). Although Yang et al. [4] has proposed a scheme for fault self-inspection in the Arduino chip of SIL-IoTs, the scheme does not take into account the information interaction between nodes, and further analysis cannot be performed for some fault situations, such as the mismatch between the current and light intensity of the solar panel.

Table 2. Comparison of research related to distributed fault detection.

Ref.	Scenario	Implement	Method	Deployment Density	Battery-Powered	Lightweight Design	Energy Consumption
[13]	Printer systems	Sensor node	Consistency check	N/A	N/A	N/A	N/A
[14]	WSNs	Simulation	Dual thresholds detection	1024/32 × 32 units	N/A	N/A	N/A
[15]	WSNs	Simulation	Improved dual thresholds detection	200/30 × 30 units	N/A	N/A	N/A
[7]	Canopy closure monitoring sensors	MSP430	Cumulative sum sliding window	200/2 × 106× 106 m22	✓	N/A	N/A
[16]	WSNs	Simulation	Improved 3-σ� test	1024/1 × 106× 106 m22	✓	N/A	N/A
[17]	Industrial control systems	Simulation	Genetic algorithms	N/A	N/A	N/A	N/A
[18]	WSNs	Simulation	Support vector machines	200/30 × 30 units	N/A	N/A	N/A
[19]	WSNs	Simulation	Dual thresholds detection	1024/2.62 × 105× 105 m22	N/A	N/A	N/A
[20]	Infrared sensors	Arduino	Exponential smoothing	N/A	✓	✓	N/A
[21]	WSNs	Simulation	Exponential smoothing and median value detection	N/A	✓	✓	N/A
	Our	Arduino	Quantile method and residual test	7/2.72 × 105× 105 m22	✓	✓	✓

Since SIL-IoTs operate in multiple interrelated ways, the distributed fault-detection strategy, which detects faults via local evidence on sensor nodes, can be applied to address these issues [5]. Furthermore, the distributed fault-detection methods in wireless sensor networks (WSNs) need to consider the computational capacity, bandwidth usage, and residual energy of nodes [22]. Therefore, the relevant literature work on such distributed fault-detection methods is worthy of reference.

Several contributions have been made over the last two decades. One of the earliest attempts can be found in [13], where consistency between local components is modeled to detect faults in discrete-event systems. In contrast to [13], Chen et al. [14] proposed a distributed fault-detection (DFD) method for measurements of WSNs by checking the number of faulty states of neighboring nodes calculated by residual analysis between neighboring nodes. In [15], a similar but slightly improved method is proposed where each node detects faults by checking the number of neighboring nodes in possibly normal states, which can be obtained by the method proposed in [14]. The results in [15] indicate that the improved method can be applied in WSNs with fewer neighboring nodes.

In [14][15], the detection threshold is predefined according to different applications at the time of deployment, which is a design parameter and highly dependent on the application and requires specific knowledge. To avoid the need for on-site technical expertise, Panda and Khilar [16] proposed a distributed self-fault-detection (DSFD) method for large-scale WSNs, where each WSNs node can identify its own faulty conditions via a modified three-sigma edit test.

The sliding window is an alternative method for detecting faults. For example, the TinyD2 method [7] has been proposed to detect faults by first calculating a cumulative sum on a sliding window. The original values are then reordered using the bootstrap method to generate a new data sequence. If a change is detected, the faulty node is identified. In addition, the TrusDet method [19] detects faults using a fused result from a sliding window, where a more recent data point has a greater influence on the data fusion. A vote is then taken to determine the status of the current area. All these approaches can be performed on sensor nodes and require few parameters. However, fault detection based on node voting results will fail if more than half of the nodes fail. In addition, their performance is affected by the number of neighboring nodes and will fail if neighboring nodes are not correlated with the target node.

Recent research has focused on correlation analysis-based fault-detection schemes, which are suitable for optimal fault detection and are characterized by their independence from expert knowledge. For instance, Hou et al. [23] applied the Jennic JN5139 sensor board and controller board to fuse decisions evaluated by three sensor nodes in a motor monitoring system. In [17][24], the spatial correlation analysis-based fault-detection methods are developed to compress the data transmitted by neighboring nodes that affect the target node. Fu et al. [20] proposed a trend correlation-based fault detection (TCFD) method, which detects faults via trend correlation analysis and the mean value of neighboring nodes. The self-starting mechanism is designed to reduce the response time of nodes to faults. In addition, Cheng et al. [25] applied space–time correlation analysis to estimate the weight value for fault detection, resulting in high detection accuracy and low false alarm rate for temperature, humidity, and voltage data. Unlike [17][24][25], Liu et al. [26] proposed a metric correlation-based distributed fault-detection method (MCDFD), which is motivated by the fact that abnormal correlations between measurement metrics indicate faults. By analyzing the metric correlation between sensor readings, the MCDFD method can reduce communication overhead and has high detection accuracy under conditions of dense distribution and high node failure rate.

References

1. Yang, X.; Shu, L.; Chen, J.; Ferrag, M.A.; Wu, J.; Nurellari, E.; Huang, K. A Survey on Smart Agriculture: Development Modes, Technologies, and Security and Privacy Challenges. IEEE/CAA J. Autom. Sin. 2021, 8, 273–302.
2. Yang, F.; Shu, L.; Huang, K.; Li, K.; Han, G.; Liu, Y. A Partition-Based Node Deployment Strategy in Solar Insecticidal Lamps Internet of Things. IEEE Internet Things J. 2020, 7, 11223–11237.
3. Guo, X.; Shu, L.; Yang, X.; Nurellari, E.; Li, K.; Du, B.; Yao, H. Two-Hop Energy Consumption Balanced Routing Algorithm for Solar Insecticidal Lamp Internet of Things. Sensors 2022, 22, 154.
4. Yang, X.; Shu, L.; Li, K.; Huo, Z.; Shu, S.; Nurellari, E. SILOS: An Intelligent Fault Detection Scheme for Solar Insecticidal Lamp IoT With Improved Energy Efficiency. IEEE Internet Things J. 2023, 10, 920–939.
5. Yang, X.; Shu, L.; Li, K.; Huo, Z.; Zhang, Y. SA1D-CNN: A Separable and Attention Based Lightweight Sensor Fault Diagnosis Method for Solar Insecticidal Lamp Internet of Things. IEEE Open J. Ind. Electron. Soc. 2022, 3, 291–303.
6. Huang, K.; Shu, L.; Li, K.; Yang, X.; Zhu, Y.; Wang, X.; Su, Q. Design and Prospect for Anti-theft and Anti-destruction of Nodes in Solar Insecticidal Lamps Internet of Things. Smart Agric. 2021, 3, 129.
7. Liu, K.; Ma, Q.; Gong, W.; Miao, X.; Liu, Y. Self-Diagnosis for Detecting System Failures in Large-Scale Wireless Sensor Networks. IEEE Trans. Wirel. Commun. 2014, 13, 5535–5545.
8. Adday, G.H.; Subramaniam, S.K.; Zukarnain, Z.A.; Samian, N. Fault Tolerance Structures in Wireless Sensor Networks (WSNs): Survey, Classification, and Future Directions. Sensors 2022, 22, 6041.
9. Zhang, Z.; Mehmood, A.; Shu, L.; Huo, Z.; Zhang, Y.; Mukherjee, M. A Survey on Fault Diagnosis in Wireless Sensor Networks. IEEE Access 2018, 6, 11349–11364.
10. Staffa, A.; Palmieri, M.; Morettini, G.; Zucca, G.; Crocetti, F.; Cianetti, F. Development and Validation of a Low-Cost Device for Real-Time Detection of Fatigue Damage of Structures Subjected to Vibrations. Sensors 2023, 23, 5143.
11. Ramanathan, N.; Chang, K.; Kapur, R.; Girod, L.; Kohler, E.; Estrin, D. Sympathy for the sensor network debugger. In Proceedings of the 3rd International Conference on Embedded Networked Sensor Systems, San Diego, CA, USA, 2–4 November 2005; pp. 255–267.
12. Tang, P.; Chow, T.W.S. Wireless Sensor-Networks Conditions Monitoring and Fault Diagnosis Using Neighborhood Hidden Conditional Random Field. IEEE Trans. Ind. Inform. 2016, 12, 933–940.
13. Su, R.; Wonham, W. Global and local consistencies in distributed fault diagnosis for discrete-event systems. IEEE Trans. Autom. Control 2005, 50, 1923–1935.
14. Chen, J.; Kher, S.; Somani, A. Distributed Fault Detection of Wireless Sensor Networks. In Proceedings of the 2006 Workshop on Dependability Issues in Wireless Ad Hoc Networks and Sensor Networks, DIWANS ’06, Los Angeles, CA, USA, 26 September 2006; Association for Computing Machinery: New York, NY, USA, 2006; pp. 65–72.
15. Jiang, P. A New Method for Node Fault Detection in Wireless Sensor Networks. Sensors 2009, 9, 1282–1294.
16. Panda, M.; Khilar, P. Distributed self fault diagnosis algorithm for large scale wireless sensor networks using modified three sigma edit test. Ad Hoc Netw. 2015, 25, 170–184.

17. Jiang, Q.; Ding, S.X.; Wang, Y.; Yan, X. Data-Driven Distributed Local Fault Detection for Large-Scale Processes Based on the GA-Regularized Canonical Correlation Analysis. IEEE Trans. Ind. Electron. 2017, 64, 8148–8157.
18. Gharamaleki, M.M.; Babaie, S. A new distributed fault detection method for wireless sensor networks. IEEE Syst. J. 2020, 14, 4883–4890.
19. He, S.; Chen, J.; Shu, Y.; Cui, X.; Shi, K.; Wei, C.; Shi, Z. Efficient Fault-Tolerant Information Barrier Coverage in Internet of Things. IEEE Trans. Wirel. Commun. 2021, 20, 7963–7976.
20. Fu, X.; Wang, Y.; Li, W.; Yang, Y.; Postolache, O. Lightweight Fault Detection Strategy for Wireless Sensor Networks Based on Trend Correlation. IEEE Access 2021, 9, 9073–9083.
21. Flynn, D.; Pengwah, A.B.; Razzaghi, R.; Andrew, L.L. An Improved Algorithm for Topology Identification of Distribution Networks Using Smart Meter Data and its Application for Fault Detection. IEEE Trans. Smart Grid 2023.
22. Brown, S.; Sreenan, C.J. Software Updating in Wireless Sensor Networks: A Survey and Lacunae. J. Sens. Actuator Netw. 2013, 2, 717–760.
23. Hou, L.; Bergmann, N.W. Novel Industrial Wireless Sensor Networks for Machine Condition Monitoring and Fault Diagnosis. IEEE Trans. Instrum. Meas. 2012, 61, 2787–2798.
24. Zhang, K.; Peng, K.; Ding, S.X.; Chen, Z.; Yang, X. A Correlation-Based Distributed Fault Detection Method and Its Application to a Hot Tandem Rolling Mill Process. IEEE Trans. Ind. Electron. 2020, 67, 2380–2390.
25. Cheng, Y.; Liu, Q.; Wang, J.; Wan, S.; Umer, T. Distributed fault detection for wireless sensor networks based on support vector regression. Wirel. Commun. Mob. Comput. 2018, 2018, 4349795.
26. Liu, Q.; Yang, Y.; Qiu, X. A metric-correlation-based distributed fault detection approach in wireless sensor networks. In Proceedings of the 2015 17th Asia-Pacific Network Operations and Management Symposium (APNOMS), Busan, Republic of Korea, 19–21 August 2015; pp. 186–191.