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Abstract: Fire pumps are the key components of water supply in a firefighting system. At present, there is a lack of fire water pump testing methods that intelligently detect faulty states. Existing testing approaches require manual operation, which leads to low efficiency and accuracy. To solve the issue, this paper presents an automatic and smart testing approach that acquires measurements of the flow, pressure, shaft power and efficiency from smart sensors via an IoT network, so that performance curves are obtained in the testing processes. An IoT platform is developed for data conversion, transmission and storage. The Discrete Fréchet Distance is applied to evaluate the similarities between the acquired performance curves and metric performance curves, to determine the working condition of the fire pump. The weights of the measurement dimensions for distance computation are optimized by the Genetic Algorithm to improve the distinction between normal and faulty performance curves. Finally, the experimental results show that the proposed method can completely detect faulty states and prove its high practicality for real firefighting systems.

Keywords: fire pumps; performance testing; performance curves; Fréchet Distance



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1. Introduction

Firefighting systems are of great importance in the safety and protection of buildings from fire accidents [1]. Traditional fire water supply systems rely on manual operation and inspection, which leads to slow responses and low reliability. Recently, smart firefighting systems have been proposed and developed due to their capability of enhancing the efficiency and effectiveness of firefighting operations. Reinforced by the Internet of Things (IoT) technologies [2,3], smart firefighting systems are able to perform intelligent and automated fire detection and suppression. IoT-based smart devices, such as smoke detectors, heat sensors, water sprinklers, etc., as well as advanced technologies such as wireless networking, smart sensors, machine learning and automation, are applied to provide intelligent monitoring, early detection and a rapid response to fire incidents.

Fire pumps are key components of a firefighting system [4]. The operating state of the fire pump determines whether the firefighting system can successfully suppress the fire. Fire pump failures and faults lead to low water supply performance, obstructing the firefighting processes, which is a critical issue that commonly occurs. Therefore, monitoring and inspecting the operating condition of fire pumps is crucial in the maintenance of firefighting systems. However, at present, most "smart" or "IoT" firefighting solutions only focus on fire detection hardware [5] and methodologies [6,7], as well as operational automation [8,9]. There is a lack of smart approaches to fire pump testing. Currently, the manual inspection of fire pumps is the conventional solution applied in fire water supply in most buildings. However, manual inspections are commonly performed annually or quarterly, due to the relatively high complexity and cost. Meanwhile, the accuracy cannot be fully guaranteed

due to the variations in the skills of the inspectors. Therefore, at present, firefighting systems are at the risk of creating an unreliable fire water supply due to the limited efficiency and accuracy of manual inspection. A smart system that monitors and inspects fire pumps and intelligently detects faulty states needs to be investigated and developed.

There are a number of faults to lead to the complete failure or performance degradation of fire pumps. The issues that commonly cause fire pump faults are listed and described in Table 1.

Table 1. Frequently occurring issues in fire pumps.

No.	Issue	Description
1	Overheating	Insufficient cooling or motor cooling system faults cause overheating that leads to motor shutdown.
2	Impeller or shell damage	Destructive objects in the pump can damage the impeller or pump shell, reducing pump efficiency.
3	Seal leakage	Leakage in pump seals causes water loss and reduces pressure reduction.
4	Bearing failures	Failed bearings lead to friction increments, overheating and pump failures.
5	Pressure switch failures	Failed pressure switches lead to a failure in starting or stopping the pump.
6	Air or cavitation	Performance reductions and potential damage are caused air or cavitation in the pump.
7	Obstructions	Water flow and pump efficiency are reduced by blockages or obstructions in the suction or discharge pipelines.
8	Insufficient water supply	Inadequate water sources or low water pressure cause a reduction in flow and pressure.
9	Freezing	Freezing temperatures cause pump damage.
10	Dirt and debris	Accumulation of dirt, debris or contaminants causes pump performance degradation.
11	Misalignment	Poor alignment of the components in the pump system causes premature wear and potential failure.

The challenges in constructing a smart fire pump testing system include the following.

- (1) Practicality: the testing system must be applied in practical firefighting applications. A testing structure and process that execute performance tests without interference in normal operation are required.
- (2) Data transmission: a data transmission platform compatible with sensing devices using different communication modes and protocols is required.
- (3) Evaluation methodology: an algorithm that accurately and efficiently detects faulty states is required.

Hence, this paper proposes a smart fire pump testing system that measures the flow, pressure, shaft power and efficiency by a set of IoT sensors and remotely inspects the condition of the fire pump in accordance with the measurements. An additional pipeline structure especially designed for testing is proposed. An analysis method distinguishing the normal and faulty states of the pump system by evaluating the acquired performance curves is presented. Compared to manual inspection, the testing system can automatically perform fire pump tests in a significantly higher frequency, and the tests can be evaluated by a unified and proven metric, so that the testing efficiency and accuracy can be improved. Integrating this testing system will ensure the water supply reliability of firefighting systems.

2. Related Work

Fire pump testing is part of the field of smart water supply, in which sensors are installed for monitoring and inspection. A smart water supply is determined by the integration of a set of products and informatics algorithms that are able to remotely and continuously monitor and diagnose problems, prioritize and manage maintenance issues and optimize all aspects of the water distribution network [10,11]. This requires limiting the energy costs, reducing water losses and improving the reliability [12,13]. The high importance of diagnostics in water supply systems and of informing operators about emergencies is emphasized. The implementation of these tasks requires the integration of a real-time remote monitoring mechanism, analysis of the collected measurement data and informatics tools identifying abnormal states [14,15]. For example, Ye et al. [13] designed an IoT-based smart water gird architecture that performed water information sensing, risk evaluation and management optimization intelligently in real time. Siew et al. [16] presented an extension of a hydraulic simulator to incorporate pressure-dependent demands. The utilization of a continuous nodal pressure-flow function coupled with a line search and backtracking procedure was applied for the improvement of the convergence rate and robustness of the algorithm. Simulations of practical water networks consisting of multiple sources, pipes, valves and pumps were successfully executed. Both normal and pressure-deficient conditions of water distribution systems can be modeled and analyzed.

Recently, IoT-based smart water supply has been integrated into Supervisory Control And Data Acquisition (SCADA) systems. Diagnostic methods are usually implemented in stages. The leakage detection methods are implemented first. Nevertheless, new methods of such detection are still being explored. Zahab et al. [17] presented a quasi-intelligent diagnostic method, integrating a SCADA system and a numerical model of the water supply system. The paper presented the effects of their implementation within the first three months of operation. Discussions of the advantages, as well as the identified limitations, recommended amendments and further developments, were also presented. Considering that the delivered water must be provided in adequate amounts and under appropriate pressure, the measurement of key attributes, such as the pressure, flow, energy, etc., of water supply systems to build diagnostic models has been recently widely investigated. These requirements necessitate the constant development of monitoring systems. Carriço et al. [18] proposed to apply four performance indices to assess energy efficiency based on the hydraulic energy balance. The implementation of this method demonstrated robustness and practicality, and the authors performed a comparison between different measures for the improvement of the energy efficiency. Stańczyk et al. [19] proposed to perform an empirical exponent analysis, determined on the basis of flow rate and pressure measurements for District Metered Areas (DMAs). Both supervised and unsupervised machine learning strategies were employed to establish an empirical exponent, and the accuracy of the operating condition qualification reached up to 90%. Li et al. [20] established a micro-smart water test bed that uses a flow sensor with an Arduino UNO and observation data model (ODM) database. Meanwhile, R-studio was employed to evaluate the performance of the micro-smart water test bed by comparing the relative errors between the experimental measurements and modeling outputs.

It can be observed that IoT-based smart testing approaches for water supply have been widely investigated and developed, both in terms of hardware and methodologies. Nevertheless, the research and development of smart fire pump testing have not been promoted thus far. Although manufacturers have already proposed fire pumps with IoT sensors so that the conditions can be remotely monitored, a method that can intelligently detect faulty states in fire pumps is still absent. There are only a small number of related studies. A similar study by Li et al. [21] investigated a fault diagnosis method for submersible pumps, but only electrical parameters were monitored and there was an absence of machine-learning-based modeling considering the comprehensive factors of faults. Du et al. [22] analyzed the effects caused by the failure of fire equipment by classifying the failure levels, but only a simple evaluation of functionalities was performed. Sobral et al. [23] proposed a periodic inspection strategy to estimate the availability of fire pumps, but the method still required multiple steps of manual analysis. Therefore, this paper proposes a smart fire pump testing system that contains both hardware for remote sensing and a method of fault detection, which is of high practicality in real implementations.

3. System Design

3.1. System Overview

The proposed system includes a fire pump with a set of smart sensors, an electric flow-control valve, a specially designed testing pipeline and an IoT network, as well as a cloud server. The architecture of the system is shown in Figure 1. The advantage of using the electric valve is to achieve automatic and remote flow control. It alters the water flow in accordance with the instructions from the cloud server via the IoT network. The testing pipeline is used only for fire pump tests so that interference in the main fire pipeline can be prevented. The IoT-based sensors measure the flow, water pressure, shaft power and power efficiency, and they upload all data to the cloud server via the IoT network. The cloud server, which remotely controls the tests, collects and analyzes testing data to evaluate the performance of the fire pump.



Figure 1. Architecture of the smart fire pump testing system.

The IoT network employs multiple communication modes, including Ethernet, Wi-Fi, cellular, LoRa, etc., in accordance with the practical communication conditions of the sensors. An IoT platform that converts and organizes data packages of different modes/protocols is designed and implemented to achieve transparent transmission between the server and the sensors. Figure 2 illustrates the architecture of the IoT platform. The platform consists of a section for general purposes of data reception, transmission, conversion and storage, as well as a section that is developed for customized computation and analysis. The platform connects to the IoT modules of the sensors directly or via edge-cloud gateways, integrating data from multiple sensors. The platform can also communicate with third-party IoT platforms.

In our case, a fire pump monitoring platform on the cloud server is constructed. On the platform, a back end for data transmission, storage, processing and analysis, as well as a front end for visualization and interaction, are developed. Figure 3 shows the web-based front end that displays the measurements from the sensors and the condition of the fire pump in real time.







Figure 3. Web-based front end of the fire pump monitoring platform.

3.2. Fire Pump Testing Process

The fire pump in the system is automatically tested online. The performance testing process is described as follows.

- (1) The cloud server transmits the flow control coefficient γ to the electric valve.
- (2) The valve adjusts the flow to reach $q = \gamma Q$, where Q is the nominal flow of the pump.
- (3) The water pressure p, the pump power P and the pump efficiency η are measured by sensors and transmitted to the cloud server.

- (4) The system repeatedly performs steps 1 to 3 by altering γ from 0.0 to 1.5 in accordance with China Standard GB 50974-2014 [24], and all coefficients and measurements are saved in the cloud server.
- (5) The cloud server forms a four-dimensional flow–pressure–power–efficiency curve that represents the performance of the fire pump at different flow conditions.
- (6) A weighted multi-dimensional distance computation is performed to achieve similarity between the tested performance curve and the metric performance curve, so that the degradation of the fire pump can be evaluated.

The metric performance curve is also obtained by steps 1 to 5, with a well-conditioned fire pump. Therefore, the performance evaluation can be illustrated. In addition, the sequence of γ is defined by the user according to the application circumstances. Higher γ values refer to higher modeling precision but also a higher computational cost. In practice, a γ sequence containing 10–15 values is commonly used in the product certification of fire pumps.

4. Performance Evaluation

To evaluate the performance degradation of a fire pump, the similarity between the acquired performance curve (APC) and the metric performance curve (MPC) is assessed. The MPC can be achieved by computing the mean of a set of normal performance curves (NPCs). Therefore, faulty performance curves (FPCs) and NPCs need to be clustered separately so that they can be clearly distinguished. To verify the condition of an APC, the distance from the APC to the MPC should not be longer than the distances from any of the NPCs to the MPC.

Figure 4 illustrates the examples of three classes of performance curves in the space, where the flow, pressure and shaft power are represented by the axes, and the efficiency is represented by a colormap. The NPC is obviously closer to the MPC than the FPC. It is illustrated that there is almost no performance degradation in the NPC, and the small differences can be considered as measurement errors. Meanwhile, compared to the MPC, the FPC reflects significant degradation, i.e., the pressure and efficiency fall remarkably as the flow increases, indicating that potential faults could occur.



Figure 4. Examples of performance curves.

4.1. Distances between Performance Curves

To quantitively estimate the similarity between curves, the Fréchet Distance [25] in the four-dimensional flow–pressure–power–efficiency space is applied. According to its

definition, the Fréchet Distance reduces as the similarity of two curves rises. In other words, NPCs have smaller Fréchet Distances to the MPC than those of FPCs. In this case, the implementation employs the Discrete Fréchet Distance [26,27], which can be presented as

$$F(x,y) = \lim_{n \to \infty, \max|t_k - t_{k-1}| \to 0} \tilde{F}^n(x,y)$$

=
$$\lim_{n \to \infty, \max|t_k - t_{k-1}| \to 0} \inf_{\alpha, \beta} \max_{t \in \{t_k\}} \{ d(x(\alpha(t)), y(\beta(t))) \}$$
(1)

where *x* and *y* are the two curves in a normalized *n*-dimensional space, and $\alpha(t)$ and $\beta(t)$ are two points sampled on *x* and *y*, respectively at time *t*. In the case of this paper, points on the curves are extracted from the measurements of the sensors. Since each curve contains the same number of measurements, the requirement in computing the Discrete Fréchet Distance can be met. We use the flow control coefficient dimension to replace the time dimension, so we can obtain

$$F(x,y) = \lim_{n \to \infty, \max|\gamma_k - \gamma_{k-1}| \to 0} F^n(x,y) = \lim_{n \to \infty, \max|\gamma_k - \gamma_{k-1}| \to 0} \inf_{\alpha,\beta} \max_{\gamma \in \{t_k\}} \{ d(x(\alpha(\gamma)), y(\beta(\gamma))) \}$$
(2)

Meanwhile, considering that measurements by different sensors should be weighted differently, we assign each dimension in the space a separate weight coefficient. Therefore, the weighted Euclidean distance between two points $U = (u_1, u_2, ..., u_n)$ and $V = (u_1, u_2, ..., u_n)$ in the space is defined as

$$d(U,V) = \sqrt{\sum_{i=1}^{n} w_i (u_i - v_i)^2}$$
(3)

where $W = (w_1, w_2, ..., w_n)$ are the corresponding weights of the dimensions. The weights are achieved by an optimization process with measurement data acquired in practical operations. In the case of this paper, every point on the curve has four dimensions, denoted as (γ, p, P, η) , so the dimensionality n = 4.

4.2. Optimization of the Weights

The target of the optimization process is to minimize the mean distance within the MPC cluster (denoted as δ) and maximize the mean distance between the two clusters (denoted as σ). Therefore, we propose the ratio of δ to σ as the optimization objective. Denote the collection of all curve clusters as **C** = { $c_1, c_2, ..., c_m$ }, where c_1 is the MPC cluster. Hence, the following presents the optimization objective *O*:

$$\delta = \frac{1}{2k_1(k_1 - 1)} \sum_{x, y \in c_1} F(x, y)$$
(4)

$$\sigma = \frac{1}{2m(m-1)} \sum_{c_i, c_j \in \mathbf{C}, i \neq j} \frac{1}{k_i \cdot k_j} \sum_{x \in c_i, y \in c_j} F(x, y)$$
(5)

$$\min O = \frac{\delta}{\sigma} \tag{6}$$

where k_i is the number of curves of class c_i . The Genetic Algorithm [28] is applied to find the best set of weights that can clearly distinguish the NPCs and FPCs, so that an APC can be correctly classified.

The process of the performance evaluation is illustrated in Figure 5.



Figure 5. Complete performance evaluation process.

5. Experiments, Results and Discussion

5.1. Experimental Configuration

We construct an experimental platform for the proposed system using existing firefighting equipment produced by C-lin Electrical Co., Ltd. (Yueqing, China), one of the institutes associated with this research. Figure 6 shows the fire pump as well as its IoTbased control cabinet applied in the experiment. The specifications of the equipment are shown in Table 2.



Figure 6. Fire pump device employed in the experiments.

Table 2. Specifications of the experimental platform.

Name	Value
Suction height	1 m
Rated pump rotational speed	2980 rpm
Rated pressure	1.2 MPa
Rated flow	85 L/s

Table 3 shows a set of measurements in the normal working state. The flow coefficient values, increasing from 0.00 to 1.50, are configured by the cloud server and transmitted to the pump. The flow, pressure, shaft power and efficiency values are the measurements acquired from the sensors. With an increase in the shaft power, the pressure remains higher

than the metric (1.2 MPa) when the flow is under the rated value, and it drops slightly when the flow is overloaded, which meets the requirement of China Standard GB 50974-2014 [24]. Meanwhile, the shaft power and efficiency continue rising as the flow increases, proving that the pump system is in a good condition.

Flow Coefficient	Flow (L/s)	Pressure (MPa)	Shaft Power (kW)	Efficiency (%)
0.00	0.00	1.28	102.74	0.00
0.15	13.87	1.26	105.88	17.00
0.30	24.14	1.26	110.48	26.30
0.45	39.97	1.24	120.17	39.70
0.60	52.39	1.24	129.69	49.90
0.75	62.35	1.23	134.32	53.90
0.80	68.59	1.21	140.41	56.80
0.90	77.67	1.20	148.86	61.30
1.00	85.47	1.20	154.76	64.00
1.10	94.64	1.19	161.89	67.20
1.20	103.19	1.16	168.75	69.30
1.35	115.52	1.12	176.52	70.90
1.50	127.80	1.06	184.34	71.80

Table 3. Measurements in the normal working condition.

To include examples of high variety in the dataset, we change the state of the system by replacing the components in different conditions. The components are used and aged, but still work normally. Therefore, a relatively high variety of NPCs can be achieved. We also obtain a set of measurement data with faults, which are described in Table 1. The faults are replicated on the experimental platform by giving corresponding conditions, e.g., installing broken impellers, blocking the testing pipeline, breaking the seal, etc. Table 4 shows how the issues are replicated in the experiments.

Table 4. Replicated issues of fire pumps.

No.	Issue	Replication
1	Overheating	Overloading the motor without cooling.
2	Impeller or shell damage	Applying damaged impellers and shells.
3	Seal leakage	Applying failure seals.
4	Bearing failures	Applying damaged bearings.
5	Pressure switch failures	Applying damaged pressure switches.
6	Air or cavitation	Injecting air into the fire pump.
7	Obstructions	Placing obstructive items in the suction and discharge pipelines.
8	Insufficient water supply	Reducing the pressure of the water source.
9	Freezing	Running the fire pump system in a freezing temperature.
10	Dirt and Debris	Applying a fire pump with heavy dirt, debris and contaminants.
11	Misalignment	Misaligning the components of the fire pump.

Hence, an FPC set is also achieved. Finally, we obtain an NPC set of 60 examples, as well as an FPC set of another 60 examples. To verify the proposed method, we randomly divide the samples into training and validation sub-datasets by 3:1, i.e., 90 training examples and 30 validation ones.

5.2. Results and Discussion

We alter the key parameters of GA, including the population, crossover probability and mutation probability, to achieve an optimal solution of the weights. The following are the considerations made in determining the key parameters.

- (1) Population: a larger population expands the search space of GA, but also increases the computational cost. Hence, under the premise of achieving high accuracy, it is expected to select a relatively small population value.
- (2) Crossover probability and mutation probability: higher values of these two parameters also expand the search range of GA, but possibly cause a local optimum, which reduces the accuracy. The two parameters are selected in accordance with the test results.
- (3) Testing values of the parameters: the testing values of the population (30, 50, 100), crossover probability (0.90, 0.93, 0.96) and mutation probability (0.10, 0.05, 0.01) are all determined by common GA parameter ranges, where optimal parameters can be found in most circumstances.

The weights are trained by the training sub-dataset and applied to the validation sub-dataset to determine the best solution. Every set of GA parameters is tested 3 times, in which different random divisions of the training and validation sub-datasets are used. Finally, we obtain the results as shown in Table 5.

Population	Crossover Probability	Mutation Probability	$O = \delta / \sigma$			Validation Accuracy		
			1	2	3	1	2	3
30	0.90	0.10	0.48	0.48	0.44	0.87	0.83	0.87
		0.05	0.43	0.48	0.46	0.90	0.87	0.90
		0.01	0.48	0.49	0.46	0.93	0.90	0.93
	0.93	0.10	0.41	0.39	0.39	0.93	0.80	0.97
		0.05	0.39	0.34	0.42	0.93	0.93	0.90
		0.01	0.38	0.34	0.37	0.93	0.90	1.00
	0.96	0.10	0.36	0.36	0.38	0.90	0.87	0.97
		0.05	0.30	0.32	0.35	1.00	0.90	1.00
		0.01	0.33	0.31	0.34	0.90	0.93	1.00
	0.90	0.10	0.39	0.33	0.36	0.97	1.00	0.97
		0.05	0.33	0.34	0.40	1.00	0.97	0.93
		0.01	0.43	0.38	0.39	0.90	0.97	0.97
	0.93	0.10	0.32	0.30	0.27	1.00	0.97	1.00
50		0.05	0.27	0.29	0.25	1.00	1.00	1.00
		0.01	0.28	0.31	0.25	1.00	0.97	1.00
		0.10	0.30	0.25	0.26	1.00	0.97	0.97
	0.96	0.05	0.28	0.24	0.23	1.00	1.00	1.00
		0.01	0.34	0.41	0.35	0.97	0.90	1.00
100		0.10	0.32	0.26	0.30	1.00	1.00	1.00
	0.90	0.05	0.30	0.28	0.24	0.97	0.97	1.00
		0.01	0.29	0.31	0.27	1.00	1.00	1.00
	0.93	0.10	0.23	0.26	0.23	1.00	1.00	1.00
		0.05	0.24	0.25	0.25	1.00	1.00	1.00
		0.01	0.30	0.29	0.23	1.00	0.97	1.00
	0.96	0.10	0.34	0.26	0.28	1.00	1.00	1.00
		0.05	0.30	0.28	0.24	1.00	1.00	1.00
		0.01	0.33	0.27	0.31	0.97	0.97	1.00
Unweighted Euclidian Distance		Distance	0.57	0.58	0.62	0.83	0.77	0.83

Table 5. Test results varied by GA configuration.

In Table 5, the optimization objective *O* represents the lowest ratio of δ to σ that indicates the highest distinction between the NPCs and FPCs. The validation accuracy shows its success in classifying APCs within the validation sub-dataset as normal or faulty states. We use both the optimization objective and the validation accuracy as metrics. It can be observed that with populations of 50 and 100, the accuracy in most conditions reaches 100%, which means that all tested FPCs can be recognized. Therefore, finally, we select a configuration with the lowest objective (0.23) and a relatively low cost (population = 50) as the best solution, as marked by the gray shading and bold text in Table 5. In this context, the crossover probability is 0.96 and the mutation probability is 0.05. Using this set of parameters, 100% detection of faulty states is achieved in all three tests with different dataset divisions, which proves the robustness of the proposed method. For real-world applications, the robustness of fault detection is related to the collection of faulty state examples. A more complete collection of faulty states can be used to construct a model with higher robustness and generalization abilities.

In comparison, we apply a Euclidian distance computation without optimized weights in Equation (2), i.e., each dimension is weighted equally in the Fréchet Distance computation, for APC classification. As shown in the bottom row of Table 5, in the three tests, the accuracies are 0.83, 0.77 and 0.83, respectively. Hence, it is proven that the proposed weight optimization method can significantly improve the accuracy in detecting faulty states in fire pumps. The effectiveness of the proposed method is verified.

6. Conclusions and Future Work

This paper proposes an IoT-based smart fire pump testing method and system that acquire measurements from sensors to form performance curves for degradation evaluation. The IoT network and platform is designed for data transmission. A method that identifies normal and faulty states using the acquired performance curves is proposed. Experiments prove that the method and system can achieve high detection accuracy in detecting faulty states.

In practice, for a specific firefighting system, the proposed fire pump testing system can be applied as follows:

- (1) Sufficient measurement data under various normal and faulty states are collected to form a large dataset of NPCs and FPCs;
- The system obtains weights for the Fréchet Distance by the proposed method using GA, as well as computing the MPC;
- (3) The system inspects the fire pump in a timely manner to obtain new APCs; the distance from every APC to the MPC and FPC is computed, to determine the corresponding state of the fire pump.

Since the entire testing process is fully automatic, tests can be executed weekly or even daily, to frequently inspect the pump state. Compared to conventional manual inspection, the proposed method achieves both high efficiency and accuracy in fire pump testing, which improves the reliability of the fire water supply. Since the hardware of the proposed system is designed to seamlessly replace traditional fire pumps in most circumstances, and the IoT sensors can all be wirelessly connected, there is low complexity in deploying such a testing system.

Nevertheless, at present, the fault detection models need to be trained separately for different types of fire pump systems. Hence, in future work, we plan to expand the database of examples in realistic working conditions via the proposed IoT platform, in order to build a general fault detection model for multiple types of fire pump systems. Meanwhile, the improvement of the modeling algorithm needs to be accomplished. The distribution of the curves in the performance space can be complicated, so different algorithms with a higher capability in distinguishing NPCs and FPCs need to be investigated.

In addition, the methodology of the proposed system is scalable to be utilized in other applications in the firefighting or water supply fields, e.g., end-water testing, leakage detection, etc. The proposed testing system can be integrated into existing firefighting systems with the functionalities of smart fire detection, automatic sprinkling and smoke exhaust, and a comprehensive firefighting framework can be constructed.

Finally, there are inevitable limitations in the proposed fire pump testing method. The implementation of the proposed testing system is limited by several factors: the requirement of IoT infrastructure leads to high costs in some circumstances; the acquisition of modeling data from users is a potential issue due to concerns about data security; and the pricing of the proposed system is higher than that of traditional fire pumps, which could raise marketing difficulties.

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