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Optimization of the Deployment of Temperature Nodes Based on Linear Programing in the Internet of Things

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Optimization of the Deployment of Temperature Nodes Based on Linear Programing in the Internet of Things

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Abstract: The Internet of Things emphasizes the concept of objects connected with each other, which includes all kinds of wireless sensor networks. An important issue is to reduce the energy consumption in the sensor networks since sensor nodes always have energy constraints. Deployment of thousands of wireless sensors in an appropriate pattern will simultaneously satisfy the application requirements and reduce the sensor network energy consumption. This article deployed a number of sensor nodes to record temperature data. The data was then used to predict the temperatures of some of the sensor node using linear programming. The predictions were able to reduce the node sampling rate and to optimize the node deployment to reduce the sensor energy consumption. This method can compensate for the temporarily disabled nodes. The main objective is to design the objective function and determine the constraint condition for the linear programming. The result based on real experiments shows that this method successfully predicts the values of unknown sensor nodes and optimizes the node deployment. The sensor network energy consumption is also reduced by the optimized node deployment.

Key words: Internet of Things; linear programming; optimized node deployment; energy consumption

1 Introduction

The Internet of Things connects objects with each other, with applications in the Internet of Things bound to be very large. Some typical applications are environmental monitoring, intelligent transportation[1], intelligent medical systems, intelligent homes, and intelligent logistics which need large numbers of sensors or Radio Frequency Identifications (RFIDs) to collect huge amounts of accurate information. Even without considering the Quality of Service (QoS), the sensors need to have clear objections and abilities to process the huge amounts of information and control the costs of a large numbers of sensors. Sensor redundancy is also important since some of these many sensors will fail. The energy consumption and processing capabilities in the nodes of the Internet of Things have affected development of the Internet of Things. Improving the processing capability or reducing power consumption of a single node is often difficult. Thus, a better idea is to optimize the network node deployment. Yun and Zhang[2] indicated that besides the heating system, the indoor temperature is mainly affected by the amount of daylight with the elevation angle of the sun, the main factor controlling the amount of light that increases the indoor temperature. Some minor reasons such as sudden climate changes and human factors have some effect but these are not the focus of this discussion. The temperatures of different locations in a room may differ due to the amount of sunlight hefting that area, so many sensor nodes are needed in a room to give an overall understanding of the indoor temperature. The optimal deployment of nodes in the Internet of Things

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(IOT) was studied by setting up an indoor temperature monitoring system in three typical rooms. Large scale monitoring of indoor temperatures will require many sensor nodes in many rooms. Deploying many sensors in a room will give a more comprehensive understanding of the indoor temperature, but the sensors need to be deployed in appropriate positions in the room and the optimal locations are difficult to determine. Here, the objective is to reduce the cost of the sensor nodes and the overall energy consumption of the Internet of Things especially for large-scale applications. More sensors will then provide more information. Analysis of the sensor temperature data shows that the temperatures of many nodes are related with each other. Too much data may adversely influence the processing efficiency and application speed. The temperature of sunny side of the room will be higher than the shaded side. Thus, the temperature of a specific location is related to the temperatures in other spots in the same area or even in different areas. With the appropriate model for this relationship, the temperature of a sensor node can be predicted from the temperatures of other nodes, and the node deployment can be optimized to reduce the number of sensor nodes, to replace temporarily disabled nodes, and to reduce the node sampling rate to reduce the node cost and the number of battery replacements.

In this study, 10 sensors were deployed in three rooms to monitor the indoor temperatures and deliver the data using a wireless multi-hop system from the sensors to a base station connected to a computer which transformed the data into Ethernet data for storage in the computer. Then, linear programming is used to predict the sensor readings based on other node readings. Optimization of the node deployment reduces the number of nodes and the node sampling rate and reduces the overall network power consumption and the number of battery replacements. The prediction capability can also be used to cope with temporary node failures in the network by predicting the temperatures of disabled sensors.

2 Related Work

Zhang et al.[3] and Wang and Cai[4] both developed information systems based on the IOT. Zhang et al. used RFID for the perception layer combined with intelligent phones, GPS, GIS, and other systems. Wang and Cai collected temperature, humidity, and pH data from the sensors. Xian et al.[5] described a real-time monitoring system to effectively improve the management of chemical laboratories and dangerous goods warehouses using a system similar to the system of Zhang et al.[3] Chang and Zhang[6] and Katabira et al.[7] proposed systems for monitoring the environment using Wireless Sensor Network (WSN) with Chang and Zhang using fuzzy logic to automatically get the best expected data while the system of Katabira et al.[7] controled the air-conditioning flow nozzle and the temperature distribution. Both sensors used the IEEE 802.15.4/Zigbee communication protocol. Many people have designed methods to reduce energy consumption in network sensors. Shi[8] focused on the optimal load balancing overlay design problem. Hu and Zhang[9] proposed a node deployment optimization method based on a genetic algorithm to improve the target detection accuracy in WSNs by calculating the global optimal solution for their optimization of the sensor positions. Hu and Zhang only used the simulations to validate the effectiveness of their algorithm. Long and Gui[10] studied the optimization of the network performance in a movement-assisted data gathering scheme by analyzing the energy consumption of wireless sensor networks with node uniform distribution. However, their research was also based on simulations.

Ren[11], Li et al.[12], and Zhang[13] used actual tests to evaluate their methods. The system of Li et al.[12] was based on the IOT and optimized the networking protocol to reduce energy usage for the whole network. Zhang[13] presented a power management scheme in their real system to save energy with the result showing that the working overhead could be reduced by 47%. Ren[11] balanced the network load to improve the network lifetime with her node deployment strategy with a carefully designed path of the mobile anchor node for better sensor positioning.

Most of these monitoring systems were aimed at monitoring and control. Different systems have different application targets, such as improving the management of dangerous goods in chemistry laboratories or warehouses[3,5] or better management of the environment for crops[4,14]. Katabira et al.[7] suggested for system control while others have focused on monitoring. Chang and Zhang[6] monitored indoor temperatures and humilities with a fuzzy-PID algorithm to get the most expected data, while Wu et al.[15] put more emphasis on real-time monitoring. Zhang[13] described a system to monitor and protect the living environment for wildlife.

Other studies sought to optimize the deployment of sensors to reduce energy consumption[9-13]. Some of the algorithms were only tested using simulations instead of real data from the sensor nodes. The priorities of most node deployment algorithms have been to increase the coverage area, to enhance the network connectivity to extend the network lifetime and to improve the data transmission accuracy. Li et al.[12] optimized the system networking protocol to reduce energy consumption. Zhang[13] used a power management scheme to reduce energy consumption and the working overhead by 47%.

The current study used an indoor temperature monitoring system with real data to validate the design using IRIS nodes. The study focuses on reducing the number of sensors and the sampling rate to save energy for the entire network in the IOT. In addition, once the system can predict the monitoring value for a sensor, the system can compensate for temporary sensor failure. IOT applications usually need many sensors. If the QoS is not a limitation, many of the sensors are not necessary because the data they monitor is redundant or is related with other data. These unnecessary nodes not only waste energy but also add to the complexity of the monitoring and controlling systems and even computations in higher level applications. In this case, the unnecessary nodes can be removed to improve the monitoring system efficiency. This article presents a prediction and location optimization method based on real monitoring data. The method uses linear programming to predict some node temperatures from other node data and sensor historical data. Accurate predictions allow removal of some nodes or appropriate reductions of the sampling rate to optimize the node deployment. Optimizing the deployment will reduce sensor energy consumption and the energy consumption of the entire sensor network.

3 Experimental Design

Katabira et al.[7] used 12 motes and 8 laser sensors. Jimenez et al.[14] used 5 Tmote Sky sensors in a greenhouse. Hu and Zhang[9] used 7 sensor nodes. Some articles do not state how many nodes were used. This study used 10 IRIS sensors selected based on the laboratory conditions and the size of the experimental site. The ten sensor nodes were deployed in three rooms with three nodes in rooms 1 and 2 and four nodes in room 3 to collect data. The three rooms were close to each other geographically with windows having different orientations. Historical data was then obtained from all the sensors and stored in the computer. The data was divided into 5 groups with 4 groups for training and 1 for testing. The five groups of data were collected around 15:50 in April in Changchun and were referred to as training 1-4 and test 2. Two more groups of data were collected for testing around 20:07 and 13:22 in April in Changchun and were referred to as test 1 and test 3. Thus, there are 4 groups of training data and 3 groups of testing data at different times. The next step was to design the objective function, calculate the constraint conditions for the equations and inequalities, and determine the constant vector. The genetic algorithm in Matlab[16] was used to solve the linear programming problem. The temperatures of the right sensor were then used to predict the test data. The main experimental steps were shown in Fig. 1.

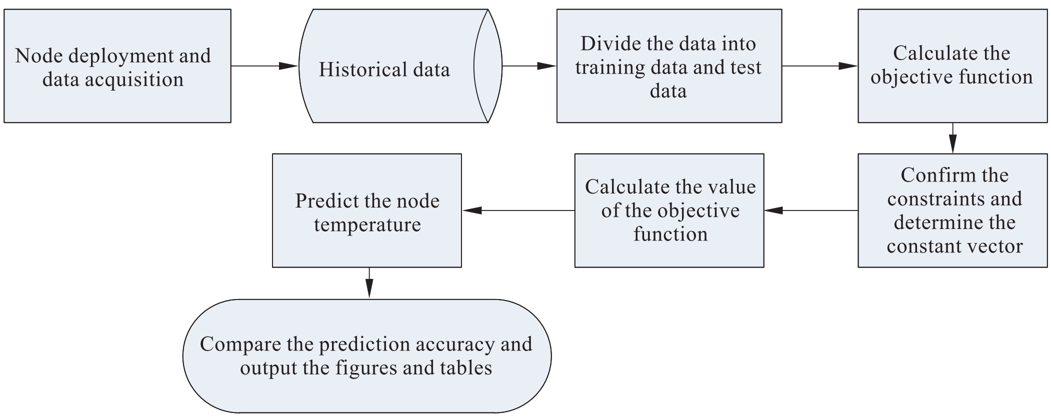

Fig. 1 Flowchart for predicting the temperatures.

3.1 Data collection

3.1.1 Node introduction

IRIS node produced by Crossbow Technology Inc. was used as the sensor node. These sensors were based on the Atmegal1281 micro-processing chip and a RF230 RF chip working at 2.4 GHz and supporting the IEEE 8.2.15.4/Zigbee communication protocol. The IRIS[17] node features several new capabilities that enhance the overall functionality of Crossbows wireless sensor networking products. The node has a three times greater radio range and twice the program memory of MICA Motes and outdoor line-of-sight tests have yielded ranges as great as 500 meters between nodes without amplification. The IRIS not only has a longer transmission distance, but also has ultra-low power consumption and, thus, a longer battery life. The IRIS is designed specifically for deeply embedded sensor networks.

3.1.2 Node deployment

Ten sensor nodes were set in three rooms as the wireless multi-hop mesh network. All of the nodes delivered messages through the wireless multi-hop mesh network with the messages finally delivered to the base station. The base station was connected to a computer through a USB data cable. The base station works as an aggregation node collecting the data monitored by the sensor nodes for transfer to the computer. The data was in the database to complete the data collection. Some of the nodes were deployed on the walls with others on the windows, so the sensor temperatures were quite different. The topology of the nodes, base station, and computer is shown in Fig. 2.

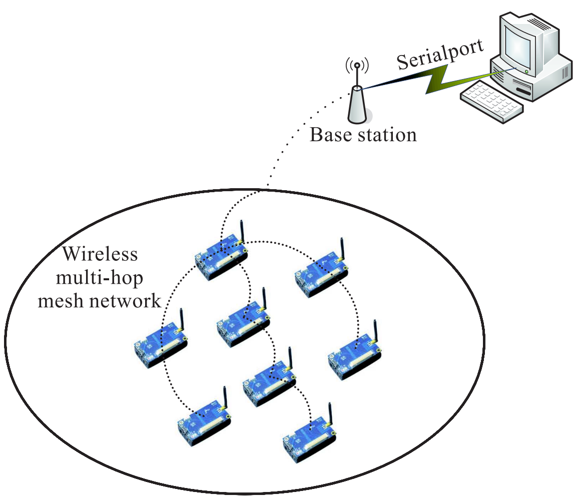

Fig. 2 Data acquisition network topology.

3.1.3 Data preprocessing

Network or node failure can occur while the sensors are delivering the data packets so some of the data may be redundant, missing or invalid. Thus, data preprocessing is necessary to remove enormous data as much as possible to reduce the influence of enormous results. The data was preprocessed according to the following rules:

(1) Remove duplicate data points which are exactly the same.

(2) When data is missing, all the data at that time point is discarded. Thus, all of the data for all ten sensor nodes are in groups.

(3) Some of the temperature data was invalid such as negative values in the summer or other similar situations.

(4) Sudden temperature changes in a credible range are retained once there may be heat sources nearby.

3.2 Linear programming

3.2.1 Standard linear programming form

The linear programming objective function is either maximized or minimized with various constraint conditions on the equations such as equations or inequalities so the form of the linear programming problem is quite uncertain. Zhang[18] gave some rules for the standard form of linear programming problem. The standard linear programming form has an objective function that is to be minimized with non-negative decision variables and non-negative constants on the right side. The problem can be expressed in the following form:

$$\text{minimize}(c_1x_1 + c_2x_2 + \cdots + c_nx_n) \tag{1}$$

with

$$\begin{cases} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n = b_1, \\ \cdots \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n = b_2, \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n = b_m, \\ x_1, x_2, \cdots, x_n \geqslant 0 \end{cases} \tag{2}$$

where $b_i \geqslant 0$ $(i = 1, 2, \cdots, m)$. Formula (1) expresses the objective function with Formula (2) expressing the constraint conditions. The standard form can be abbreviated as:

(1) Matrix form:

$$\text{minimize} = \boldsymbol{cx} \tag{3}$$

with

$$\begin{cases} \boldsymbol{Ax} = \boldsymbol{B} \\ \boldsymbol{x} \geqslant \boldsymbol{0} \end{cases} \tag{4}$$

(2) Vector form:

$$\text{minimize} = \boldsymbol{cx} \tag{5}$$

with

$$\begin{cases} \sum_{j=1}^{n} x_j \boldsymbol{P}_j = \boldsymbol{B}, \\ x_1, x_2, \cdots, x_n \geqslant 0 \end{cases} \tag{6}$$

where

$$\boldsymbol{c} = (c_1, c_2, \cdots, c_n),$$

$$\boldsymbol{A} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix},$$

$$\boldsymbol{B} = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{pmatrix},$$

$$\boldsymbol{x} = (x_1, x_2, \cdots, x_n),$$

$$\boldsymbol{P}_j = \begin{pmatrix} a_{1j} \\ a_{2j} \\ \vdots \\ a_{mj} \end{pmatrix}.$$

3.2.2 Data analysis

The data consisted of 3500 data points altogether for 10 sensors. 2000 data points were used as the tested training data with the remaining 1500 points used as the test data in 3 groups. The first step was to assure the objective function and constraint conditions, which is a key step. The objective function should be relatively stable so that the accuracy of the predicted values should be only fluctuating small amount as the test data changes. Various factors can affect the temperature differences between the sensors, such as the room size, the appearance of new heat sources, and different amounts of sunlight in the room. Yun and Zhang[2] pointed out that, in addition to the heating system, the indoor temperature is mainly affected by the amount of sunlight when the solar elevation angle is constant. The data in Fig. 3 shows that the fluctuations in the sensor nodes differ with the temperatures of the sensors on the windows changing faster than those on the wall. The temperature extremes shown in Fig. 3 show the temperature ranges for the ten sensors for the training data. Based on the analysis above, the calculation method for coefficients c_i in Formula (1) can be specified artificially as:

$$\begin{cases} c_i = \dfrac{d_{10}}{d_i}, 1 \leqslant i \leqslant 9; \\ c_{10} = -\sum_{j=1}^{9} c_j \end{cases} \tag{7}$$

where d_i expresses the average temperature of sensor i.

After defining the objective function, the next step is to determine the constraints for the equations. The location factors are taken into account as relationships between the sensors in the same room or between sensors on the window or on the wall. The sensors in the same room usually have similar temperatures. Also, sensors on the windows often receive more direct sunlight than the sensors on the walls so that more sunlight will result in higher temperatures[1]. Thus, their temperature differences can be used as constraint conditions. In addition, the average temperature can also be used as an equation. Thus, there are a total of 13

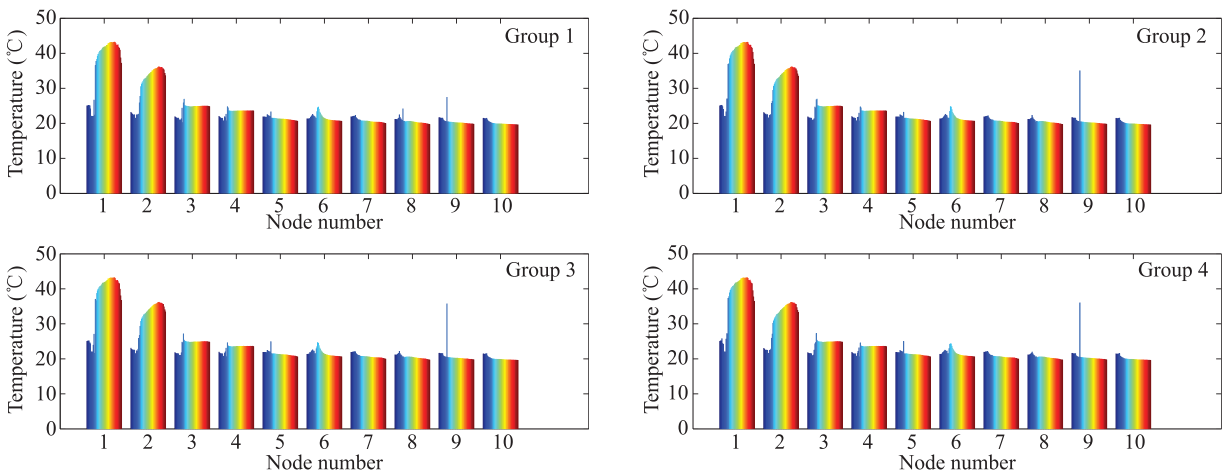

Fig. 3 Training data.

inequalities as the constraint conditions. The constraint conditions are expressed as a coefficient matrix $\boldsymbol{A}$ and a constant vector $\boldsymbol{B}$:

$$\boldsymbol{Ax} \leqslant \boldsymbol{B} \tag{8}$$

$$\text{where}\ \boldsymbol{A} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & 0 & -1 & -1 & -1 & 0 & 0 & 0 \\ -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & -1 & -1 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 1 \\ -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 \end{pmatrix},$$

$$\boldsymbol{B} = \begin{pmatrix} 249.83 \\ -120.35 \\ -150.97 \\ 188.59 \\ 66.56 \\ 78.47 \\ 148.91 \\ -39.70 \\ -40.62 \\ -40.22 \\ -39.40 \\ -42.41 \\ -42.56 \end{pmatrix}.$$

Only the constant vector of group 1 is listed here, since the vectors are similar.

The genetic algorithm in Matlab is used with these coefficients and the training data to calculate the objective function. The objective function does not have physical meaning but is still useful. The objective is to improve the prediction accuracy.

The last step is to predict the value at a specific node using the objective function result with the known minimum and the coefficients of the objective function with $n-1$ of the n variables x_i in Formula (1). The unknown sensor temperature can be found from

$$x_n = \frac{c_1x_1 + c_2x_2 + \cdots + c_{n-1}x_{n-1} - \text{mins}}{c_n} \tag{9}$$

where “mins” represents the calculated minimum value in Formula (1).

3.3 Result analysis

The 3500 temperature data points for the ten sensors in three rooms included 2500 points taken around 15:50 which were divided into 5 groups with the continuous five sets of data are allocated into different groups with the timestamp differences in each group being in multiples of 5. The remaining 1000 points collected at different times were assigned to two groups. The 5th sensor was selected as the unknown based on how the average temperature decreased. The test data for the 5th sensor is shown in Fig. 4.

The objective function results for the four groups are listed in Tables 1-3 while the prediction accuracies are shown in Figs. 5-7.

As can be seen in Fig. 6, the result for test 2 is satisfactory with the prediction accuracy ranging from 89.41% to 99.98%. The average accuracy is

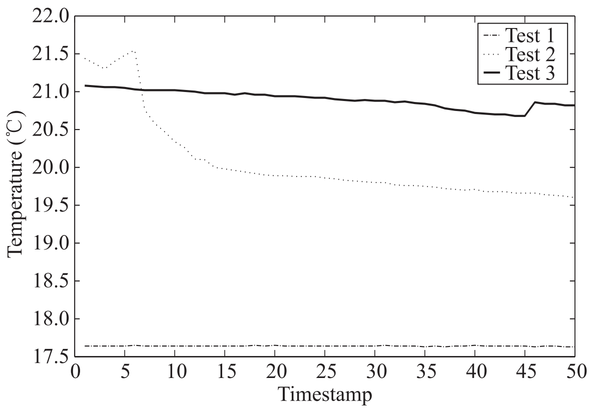

Fig. 4 Test data for the fifth node used for predictions.

Table 1 Objective function results for test 1 training data.

	Objective function minimum	Average prediction accuracy (%)
Group 1	20.78	90.59
Group 2	20.55	90.59
Group 3	20.66	89.88
Group 4	20.70	92.48

Table 2 Objective function results for test 2 training data.

	Objective function minimum	Average prediction accuracy (%)
Group 1	20.73	97.62
Group 2	20.72	97.83
Group 3	20.67	96.31
Group 4	20.68	96.78

Table 3 Objective function results for test 3 training data.

	Objective function minimum	Average prediction accuracy (%)
Group 1	20.70	89.58
Group 2	20.70	89.73
Group 3	20.72	87.35
Group 4	20.62	87.85

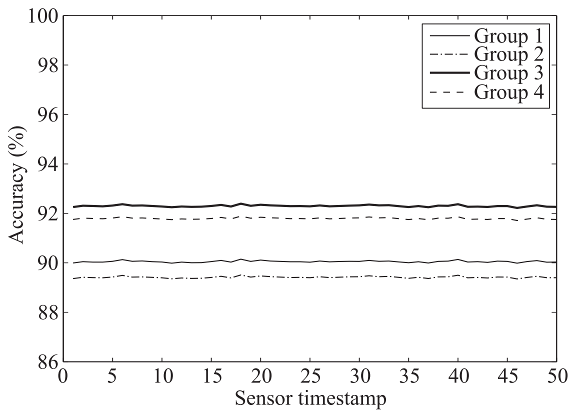

Fig. 5 Prediction accuracy for sensors for test 1 training data.

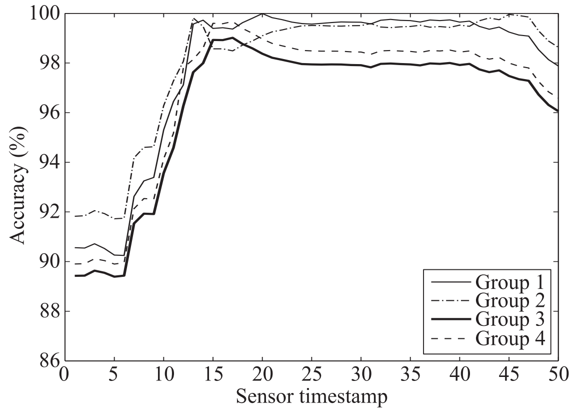

Fig. 6 Prediction accuracy for sensors for test 2 training data.

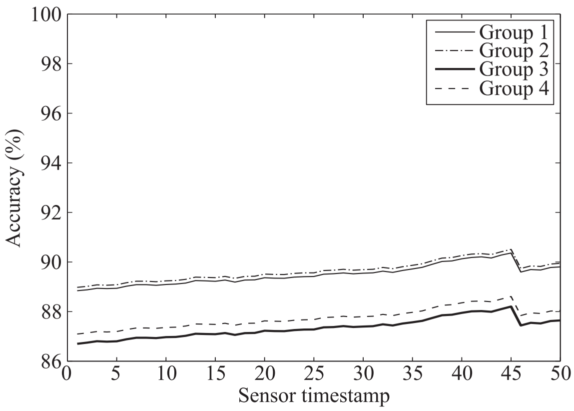

Fig. 7 Prediction accuracy for sensors for test 3 training data.

97.07%. However, for test data 1 and 3 in Figs. 5 and 7, the average accuracy dropped to 91.47% and 88.63% because at the different times of day, the temperature ratios between sensors differed. In this case, historical data can be used to predict the sensor temperatures for the same time of day. The prediction accuracy will be slightly lower for different times of day.

In each season, the temperatures of a point are similar at the time of day. In the IOT, the sensor power consumption is related to its sampling rate with high sampling rates having high power consumption. This model provides a method to appropriately reduce node sampling rates. High frequency sampling can be used for a short time, for example, for one day. After enough historical data is collected, the data can be used to reduce the sampling rate of some nodes.

In addition, if a node becomes disabled, the temperature can be easily predicted as long as there is historical data for all the sensors and current data for the other sensors in the current time. This method can also be used to reduce the number of nodes deployed for long-term monitoring with all these methods reducing energy consumption.

Thus, this analysis can be used to predict the data for any node given the right training data for the circumstance with current data from other nodes.

4 Conclusions

The model in this article makes use of historical data and current data from other sensors to relatively accurately predict a sensor's temperature with an average prediction accuracy of 97.0%.

The method provides another way to optimize sensor deployment to reduce sensor energy consumption in addition to similar studies[8-10, 13, 14]. Successful predictions of sensor temperatures mean that the number of sensors can be reduced, the sampling rate can be reduced, and even temporary sensor failure can be covered. This can also be used to optimize the sensor deployment and reduce battery power consumption and the number of battery replacements.

A quantitative analysis of how to reduce the sampling rate will require testing with much more historical data.

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