Diagnosis of computer cooling performance based on multipoint temperature measurements

Tomoyuki SUZUKI* and Tomonao TAKAMATSU*
*Toshiba Research & Development Center
1 Komukai Toshiba-cho, Saiwai-ku, Kawasaki, 212-8582, Japan
E-mail: tomoyuki11.suzuki@toshiba.co.jp

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Abstract
We propose a method for inferring the condition of factors influencing the temperature of heat-generating components in electronic equipment. Here, “factor” includes cooling components (fans, heat sinks, etc.), intake temperature, and the caloric value of the heat-generating component. The performance of these cooling components is reduced by unusual use or deterioration due to aging such as clogging or evaporation of grease. Such factors raise the temperature of heat-generating components. High temperatures of heat-generating components lead to system failure or a shortened life of the electronic equipment. Detecting decreases in the performance of cooling components allows timely provision of the required maintenance, possibly leading to increased product reliability. However, monitoring temperature alone is insufficient. The temperature of heat-generating components is also affected by factors such as intake temperature, and caloric value. In this study, we develop a method for inferring the condition of each factor influencing temperatures by using sensors installed at multiple locations. In this method, the effect of each factor on temperature depends on location, and the condition of each factor is expressed as a multivariate function using temperatures at multiple locations. The condition of each factor can then be inferred by measuring only temperatures. Furthermore, we can develop the method simply by mounting several temperature sensors on the board, making the method easy to implement. System failures can thus be prevented by performing maintenance based on the monitored factors. We conducted verification experiments using a computer to confirm the benefits of this method. In the case of inferring the conditions of four factors using four temperature sensors, the mean accuracy exceeded 90%.

Key words: Performance diagnosis, Anomaly detection, Health monitoring, Electronic equipment, Condition based maintenance, Maintenance

1. Introduction
Electronic equipment underpins many aspects of contemporary society, but system failures can cause serious damage. A principal cause of system failure is hardware malfunctions attributable to heat. Hardware is designed to operate within a certain temperature range, with cost and size taken into account. This is called thermal design. The performance index generally used for thermal design is thermal resistance, and the means of cooling for achieving the target thermal resistance, which is given by caloric value, ambient temperature, and permissible temperature of a heat-generating component, must be considered. Cooling components include heat sinks, heat pipes, and fans.

The performance of these components is reduced by unusual use or deterioration attributable to age such as clogging due to dust or obstacles or evaporation of grease. This is accompanied by a rise in the thermal resistance and the temperature of heat-generating components. Unnecessary temperature rise due to performance deterioration of cooling components should be avoided, because the rate of material degradation depends strongly on temperature, as is known from the Arrhenius equation. Thus, along with thermal design, maintaining performance of the cooling components is also important.

Maintenance can be classified into unplanned maintenance and planned maintenance (Duffuaa et al., 2001).
Unplanned maintenance is maintenance performed after failure, planned maintenance is maintenance done before failure. There is a planned maintenance technique called Condition-Based Maintenance (CBM). CBM recommends maintenance decisions based on the information collected through condition monitoring (Ahmad and Kamaruddin, 2012). CBM is performed based on platforms such as Prognostic and Health Management (PHM). According to Wang et al. (2015), PHM comprises technologies and methods for evaluating the reliability of products in situ to determine the presence or absence of failure, and mitigate system risk. It can be applied not only to reliability evaluation of a current product but also to determine product collection and disposal (Wang et al., 2015). In order to realize this technique, condition (the performance of cooling components) monitoring is important, and it must be performed continuously by means of sensors etc.

However, it is hard to detect decreases in the performance of cooling components. Figure 1 shows factors that influence temperature. The temperatures of the heat-generating components are also affected by intake temperature, which depends on the installation environment. They are also affected by caloric value, which depends on usage conditions. The installation environment and usage conditions differ among applications. Consequently, when the performance of a cooling component decreases, it is not always the case that the temperature of the heat-generating component exceeds the permissible temperature. Monitoring the temperature alone is therefore insufficient. Furthermore, a sensor that directly measures the performance of cooling components may pose problems in terms of cost or technical feasibility.

Methods for detecting performance deterioration of cooling components have been developed. Most studies determine the presence or absence of failure by comparing observed values with predefined health conditions. Hirohata et al. (2011) introduced index \( q \), which is the ratio of temperature difference between two points on the substrate and the heating value calculated from CPU utilization based on a hierarchical statistical model. They discriminate cooling performance degradation of a notebook PC by comparing the distribution of the index \( q \) in operation and in normal state defined in advance. Kumar et al. (2010) proposed a Mahalanobis distance-based diagnostic approach that employs a probabilistic approach to establish thresholds to classify a product as being healthy or unhealthy. They transformed Mahalanobis distance of observed data in the normal state to variable \( x \) by statistical processing and constructed a control chart with the summary statistics of \( x \). They detected a fault of a notebook PC by comparing the trends and bias of the observed values in operation with the control chart.

We adopted an approach different from the above methods, and developed a method to indirectly measure the performance of cooling components that could not be directly measured using temperature sensors installed at multiple locations. It is possible to infer not only each cooling component’s performance but also the condition of the installation environment such as intake temperature. In this method, the effects of factors on temperature depend on location, and the condition of each factor is expressed as a multivariate function using the temperature at multiple locations. Real-time monitoring of cooling component conditions and condition-based maintenance can prevent system failures and unnecessary temperature rise.

Fig. 1 Factors that influence temperature
2. Method for diagnosing cooling performance

Figure 2 shows electronic equipment cooled by forced convection. The equipment includes heat-generating components cooled by components such as fans and heat sinks. Temperature at an arbitrary location in the electronic equipment is affected by the conditions of the cooling components, the intake temperature, and the caloric value of the heat-generating components. These influences are defined as “factors”. The effect of each factor on temperature depends on location. For example, temperature \( T_A \), located close to heat-generating component A in Fig. 2, is more strongly affected by the condition of that component than it would be at other locations. In contrast, temperature \( T_B \), located far from heat-generating component A, is only weakly affected by the condition of the component, and temperature \( T_B \) is affected by other factors such as the condition of inlet A.

![Fig. 2 Electronic equipment cooled by forced convection](image)

The diagnosis of cooling performance employs the location-dependent effect of each factor on temperature, as shown in Fig. 3. For example, suppose that we would like to monitor the condition of factor A in Fig. 3. Temperature \( T_1 \) is more strongly affected by the condition of factor A than it would be at other locations. However, temperature \( T_1 \) is also affected by other factors. Therefore, monitoring only temperature \( T_1 \) is insufficient for monitoring the condition of factor A. Thus, we attempt to cancel out the effects of factors other than factor A by using temperatures at other locations. By doing so, the condition of factor A is expressed as a multivariate function using the temperatures at multiple locations (the “inferential function”).

If the interaction between factors is small, the inferential function of the factors is represented as

\[ x_j = g(T_i) \]

\[ T_i = f(x_j) \]

where \( x_j \) is condition of factor \( j \), \( \gamma_i \) are coefficients, and \( T_i \) is temperature at location \( i \). It is important to place temperature sensors at locations where diagonal elements of the matrix are greater than the non-diagonal elements. For example, \( T_1 \) is most strongly affected by \( x_A \). The number of inferable factors is the same as the number of temperature sensors. We must obtain the coefficients \( \gamma_i \) by experiment or numerical analysis in advance, such as during design development. Equation (1) shows that the conditions of the factors can be inferred by measuring only temperatures. A sensor other than the temperature sensor may be used. If a sensor that depends only on condition of a specific factor such as CPU utilization or fan speed is available, it can be used instead of the temperature sensor to infer the condition of the factor with higher accuracy. In other words, this method is a new technique that can detect performance deterioration of cooling components without measuring CPU utilization or fan speed directly. This method is particularly effective when the factors affecting the temperature of the target system or component can be predicted. Therefore, it can be applied regardless of cooling method (natural air cooling, forced air cooling, etc.). However, this method is not effective when the effect of each factor on temperature is the same in the area where sensors are installed. For example, if the thermal conductivity of a material is very high, the temperature in the material will be almost the same.

3. Verification experiments

This section describes the effectiveness of cooling performance diagnosis by verification experiments using a computer manufactured by Toshiba Corporation.

3.1 Experimental method

Figure 4 shows the inner structure and factors of the computer. The external form of this computer is W 115 mm x H 310 mm x D 365 mm. The caloric value of heat-generating component A, which is one of the main heat-generating components, is several tens of W. Heat-generating component A is cooled by using heat sink A with a surface area of about 0.06 m². A cooling fan is of the push type, and the air flow rate is about 0.4 m³/min under the normal condition (cooling performance is normal). In these experiments, we inferred the conditions of four factors by using four...
temperature sensors on the board. The four factors are the intake temperature, inlet A, heat sink A, and heat-generating component A, all of which are highlighted in bold red in Fig. 4. Although temperature is also affected by five other factors, which are shown in black in Fig. 4, we did not infer those conditions because the number of installable temperature sensors was limited. These five factors disturb the robustness of the cooling performance diagnosis.

Figure 5 shows sensor layouts. Type K thermocouples were used as temperature sensors. Sensor layout 1 is determined based on the results of thermal fluid analysis and knowledge about transport phenomena. Temperatures of sensors are affected by each factor, but the degree of effect on temperature depends on sensor location. Sensors in layout 2 are located far from the heat-generating component A and heat sink A, which are factors. We evaluated the influence of temperature sensor locations by comparing two patterns.
Coefficients of the inferential function are obtained before the verification experiments. The inferential function of the four factors is represented as

\[
\begin{bmatrix}
  x_{IT} \\
  x_{I_A} \\
  x_{HS_A} \\
  x_{HGC_A}
\end{bmatrix} = \begin{bmatrix}
  1.6 & -0.8 & 0.2 & 0.1 \\
  -1.4 & 2.1 & 0.0 & -0.6 \\
  0.1 & 0.1 & 0.8 & -0.7 \\
  -0.7 & -0.2 & -0.2 & 1.0
\end{bmatrix} \begin{bmatrix}
  T_1 \\
  T_2 \\
  T_3 \\
  T_4
\end{bmatrix} + \begin{bmatrix}
  16.6 \\
  6.2 \\
  2.5 \\
  2.2
\end{bmatrix}
\]

(2)

for sensor layout 1, and as

\[
\begin{bmatrix}
  x_{IT} \\
  x_{I_A} \\
  x_{HS_A} \\
  x_{HGC_A}
\end{bmatrix} = \begin{bmatrix}
  -0.3 & 0.3 & 2.6 & -2.4 \\
  -0.2 & 0.7 & 1.3 & -1.7 \\
  -2.8 & 3.3 & 17.1 & -17.3 \\
  0.2 & -1.0 & -3.7 & 4.3
\end{bmatrix} \begin{bmatrix}
  T_1 \\
  T_5 \\
  T_6 \\
  T_7
\end{bmatrix} + \begin{bmatrix}
  13.3 \\
  5.2 \\
  75.1 \\
  -14.2
\end{bmatrix}
\]

(3)

for sensor layout 2, where subscripts \( IT, I_A, HS_A, \) and \( HGC_A \) denote intake temperature, inlet A, heat sink A, and heat-generating component A, respectively. \( T_1 \) through \( T_7 \) are temperatures at different locations on the board. The coefficients of Eqs. (2) and (3) show the values rounded off to third and second decimal places, respectively. The diagonal elements of the matrix in Eq. (2) are greater than the non-diagonal elements. This is not the case in Eq. (3), because in Eq. (2) the temperatures at locations corresponding to the diagonal element of the matrix are strongly affected by the condition of the factor to be inferred. We cancel out the effects of factors other than the inferring factor by using the temperatures at locations corresponding to the non-diagonal elements of the matrix, in the same way as in Fig. 3.

There were thirty experimental conditions in the verification experiments. In each experiment, the computer continued operation until the time variation in temperature was sufficiently small, and the average value during the last five minutes was acquired as the representative temperature of each sensor. The representative temperature of each sensor was substituted into Eqs. (2) and (3) to estimate the conditions of four factors (the bold red text in Fig.4). We compared the true values, which are the experimental conditions, and the inferred values calculated by Eqs. (2) or (3) for 30 experimental conditions. We describe the inferred accuracy in section 2 of chapter 3. Table 1 shows the level of the condition of the factors. The condition of each factor was normalized in the range from 0.0 to 1.0. The magnitude of values representing the conditions of the factors denotes the impact on temperature. In the case of inlet A, 0.0 represents a non-clogged condition, and 1.0 represents a clogged condition. Table 2 shows some of the experimental conditions. Each experimental condition shown in Table 2 is a combination of the level of the conditions of the factors shown in Table 1. All experimental conditions of the nine factors in Fig. 4 were unique.

| Factors                  | Conditions |
|-------------------------|------------|
|                         | Intake temperature | 0.0 | 0.5 | 1.0 |
|                         | Inlet A        | 0.0 | 0.1 | 0.3 | 1.0 |
|                         | Heat sink A    | 0.0 | 0.1 | 0.4 | 1.0 |
|                         | Heat-generating component A | 0.0 | 0.4 | 0.6 | 0.8 | 1.0 |
| Disturbance             | Inlet B        | 0.0 | 1.0 |
|                         | Outlet A       | 0.0 | 1.0 |
|                         | Outlet B       | 0.0 | 0.4 | 0.6 | 1.0 |
|                         | Heat sink B    | 0.0 | 1.0 |
|                         | PCI slot       | 0.0 | 1.0 |
3.2 Method of calculating accuracy

The inferred accuracy of the inferential functions in Eqs. (2) and (3) is calculated as

\[ \alpha_j = \frac{1}{\exp(E_j)} \]

\[ E_j = \frac{1}{n} \sum_{k=1}^{n} E_{jk} \]

\[ E_{jk} = \frac{|x_{jk,\text{inf}} - x_{jk,v}|}{\Delta x_{j,v}} \]

where \( \alpha_j \) is the inferred accuracy of factor \( j \), \( E_{jk} \) is error between the inferred value and the true value (setting condition) of factor \( j \) of the \( k \)th experiment, and \( \Delta x_{j,v} \) is the range of conditions of factor \( j \) (1.0 in these experiments).

4. Results

4.1 Monitoring by temperature alone

Table 3 shows some of the representative temperatures of each sensor. Experiment numbers correspond to Table 2. The representative temperatures of each sensor show the values rounded off to first decimal places. As shown in Table 3, \( T_3 \) had high temperature of 51°C in experiment number 5 where the condition of heat sink A is 1.0. However, temperature \( T_3 \) is also affected by other factors. Therefore \( T_3 \) had high temperature of 50°C even in experiment number 2 where the condition of heat sink A is only 0.4.

| Experimental No. | 1   | 2   | 3   | 4   | 5   | 6   | ⋯  | 30     |
|------------------|-----|-----|-----|-----|-----|-----|-----|--------|
| Temperature at location 1, \( T_1, \)°C | 29  | 24  | 19  | 22  | 20  | 19  | ⋯  | 17     |
| Temperature at location 2, \( T_2, \)°C | 44  | 36  | 25  | 35  | 28  | 27  | ⋯  | 22     |
| Temperature at location 3, \( T_3, \)°C | 43  | 50  | 32  | 42  | 51  | 27  | ⋯  | 24     |
| Temperature at location 4, \( T_4, \)°C | 42  | 39  | 24  | 40  | 32  | 24  | ⋯  | 21     |
| Temperature at location 5, \( T_5, \)°C | 42  | 34  | 25  | 33  | 26  | 27  | ⋯  | 22     |
| Temperature at location 6, \( T_6, \)°C | 40  | 35  | 28  | 34  | 30  | 30  | ⋯  | 25     |
| Temperature at location 7, \( T_7, \)°C | 39  | 33  | 25  | 33  | 27  | 27  | ⋯  | 22     |
Figure 6 shows the relation between the true value (setting condition) and the temperature at location 3 ($T_3$). Figure 6 shows that there is poor correlation between them, because the temperature at location 3 ($T_3$) is affected by many factors. It is therefore too difficult to monitor the factor conditions by temperature alone.

4.2 Monitor by inferred value

Figure 7 shows the relation between the true and inferred values for sensor layout 1. The horizontal axis denotes the inferred value, and the vertical axis denotes the true value. The only difference from Fig. 6 is the meaning of the horizontal axis. Unlike in the case of monitoring by temperature alone, there is a strong correlation between the true value and the inferred value.

It was difficult to exactly match the condition of the intake temperature to the experimental condition. Therefore, we plotted corrected values based on measurements of the intake temperature as the true value. For this reason, the data took various values on the vertical axis in Fig. 7(a). The dotted line in Fig. 7 indicates the position of $E_j=0$. Figure 7 shows that the inferred values agree well with the true values, because many data points are plotted near the dotted line.
Table 4 shows the inferred accuracy of the four factors for sensor layout 1. The mean inferred accuracy of four factors was 92%.

| Factors               | $x_i$ | $a_i$, % |
|-----------------------|-------|----------|
| Intake temperature    | $x_{IT}$ | 96       |
| Inlet A               | $x_{I_A}$ | 82       |
| Heat sink A           | $x_{HS_A}$ | 94       |
| Heat-generating component A | $x_{HGC_A}$ | 97       |

Table 4 Inferred accuracy of the four factors for sensor layout 1

Figure 8 shows the relation between true and inferred values, and Table 5 shows the inferred accuracy of the four factors. Figure 8 and Table 5 are the results for sensor layout 2. Figures 8(c) and (d) show that the inferred values disagree with the true values. This is because sensor layout 2 has no sensor that is strongly affected by heat-generating component A or heat sink A, as Fig. 5(b) shows.

| Factors               | $x_i$ | $a_i$, % |
|-----------------------|-------|----------|
| Intake temperature    | $x_{IT}$ | 94       |
| Inlet A               | $x_{I_A}$ | 67       |
| Heat sink A           | $x_{HS_A}$ | 1        |
| Heat-generating component A | $x_{HGC_A}$ | 41       |

Table 5 Inferred accuracy of the four factors for sensor layout 2
4.3 Trends in true and inferred values

Figure 9 shows the trend in true and inferred values based on four factors: intake temperature, inlet A, heat sink A, and heat-generating component A. Figure 9 shows the results for sensor layout 1. This experiment is unrelated to the verification experiments. We changed the conditions of the nine factors in various ways, including disturbances of the five factors. As seen from Fig. 9, when the computer was stopped (from shutdown to start up), the error between the true and inferred values was large. This was because temperatures at all locations in the computer were near the ambient temperature during the stoppage. In other words, the diagnosis of cooling performance is not applicable to situations in which temperatures are the same regardless of location. Figure 9 shows that the error between the inferred and true values of intake A sometimes temporarily increases when any of the factors change rapidly. However, the inferred value of the condition for a given specific factor is hardly affected by the conditions of the other factors. Furthermore, when the conditions of some factors are simultaneously changed, the results can be inferred almost exactly.

Fig. 9 Trend of true value and inferred value of the four factors
5. Conclusions

We proposed a method for inferring the condition of factors influencing the temperature of heat-generating components in electronic equipment. Using this method, it is possible to infer not only each cooling component’s performance but also the condition of the installation environment such as intake temperature. In this method, the effect of each factor on temperature depends on location, and the condition of each factor is expressed as a multivariate function using the temperatures at multiple locations. We can implement the method by simply mounting several temperature sensors on the board, and so the proposed method is easily implemented. Furthermore, real-time monitoring of the conditions of cooling components and condition-based maintenance can prevent system failure. This method is particularly effective when the factors affecting the temperature of the target system or component can be predicted. Verification experiments using a computer confirmed the benefits of this method. When inferring the conditions of four factors by four temperature sensors, the mean accuracy exceeded 90%.

Nomenclature

\[ x \] condition of factor
\[ \gamma \] coefficient
\[ T \] temperature
\[ a \] inferred accuracy
\[ E \] error between inferred value and true value
\[ \Delta x_{i,\text{tr}} \] range of condition factor \( i \)

Subscripts

\( \text{IT} \) intake temperature
\( I_A \) inlet A
\( HS_A \) heat sink A
\( HGC_A \) heat-generating component A

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