Controller Design for Air-conditioners Considering of Occupant's Requests by using Bayesian Network

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Abstract

This paper describes a controller design for air-conditioner considering of occupant's requests, especially, a method to predict occupant's requests by using Bayesian networks. To show our basic concept and detailed procedure, the structure of Bayesian networks for this application is described. Then, probability tables which present the probabilistic distribution of occupant's requests at each temperature width are shown. After that, using an example case, we describe detailed procedure of our framework. How to predict occupant's requests and how to update probability tables are shown in detail. Finally, we confirm our proposed method discussing our experimental results.

Keywords: controller design, air-conditioning, thermal comfort, bayesian network, user modeling

1 Introduction

This paper describes air-conditioning controller design based on prediction of occupant's requests using Bayesian networks. Generally, air-conditioners control air condition based on human thermal comfort level which is defined using seven factors, such as air temperature, relative humidity, air speed, radiant temperature, metabolic rate, and clothing insulation. Well-known thermal indices are the effective temperature (ET), the wet-bulb globe temperature (WBGT), the discomfort index (DI), the predicted mean vote (PMV), the standard effective temperature (SET), and so on [1]. To control air condition, occupant's requests are predicted from the indices. However, since these indices are all generalized indices based on the experiments using numbers of subjects, they often provide wrong predictions due to the differences among individuals. Since our prediction is based on the probability tables acquired from occupants' votes, our framework can predicts occupant's requests considering of the differences. To show our basic concept and detailed procedure, we describe the structure of Bayesian networks for the prediction of occupant's requests. Next, the probability tables which present probabilistic distribution of occupant's requests at each temperature width are shown. After that, using an example case, we describe detailed procedure of our framework. How to predict occupant's requests and how to update probability tables are shown in detail. Finally, we confirm our proposed method discussing our experimental results.

2 Bayesian network modeling of occupant's requests

A Bayesian network is a directed graphical model for representing conditional independencies between a set of random variables. It provides a tool for dealing with two

Table 1 Prior probability

Operation	Probability distribution	T_1
Up	0.33	0.030
Down	0.33	0.063
Keep	0.33	0.180

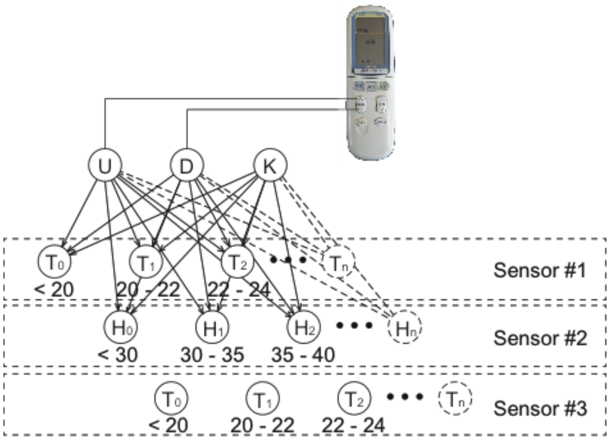

Fig.1 Bayesian network model

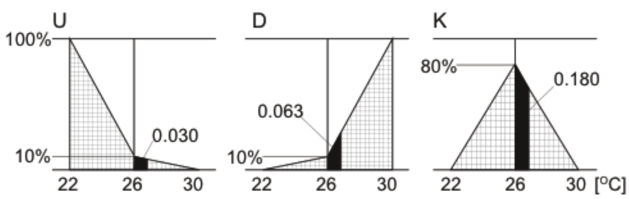

Fig. 2 Probability distribution

problems that occur through applied mathematics and engineering [2]. In the Bayesian network, an arc from node A to B can be informally interpreted as indicating that A "causes" B [3]. The simplest statement of conditional independence relationships encoded in a Bayesian network can be stated as follows: a node is independent of its ancestors given its parents, where the ancestor/parent relationship is with respect to some fixed topological ordering of the nodes. Therefore, for a Bayesian network consisting of n nodes $(x_1, x_2, ..., x_n)$, we have the representation for the joint probability distribution

$$p(x_1, x_2, ..., x_n) = \prod_{i=1}^{n} p(x_i | x_{P_i}) \tag{1}$$

where $p(x_i | x_{P_i})$ is the local conditional probability distribution associated with node i and P_i is the set of indices labeling the parents of node i (P_i can be empty if node i has no parents).

Figure 1 shows Bayesian network model of occupant's requests. In order to account for this model, let us assume that an occupant operates the air conditioner in some thermal environment. The occupant can control the air conditioner pushing buttons on the control panel. In this case, we assume that the occupant can control just up and down preset temperature. Letters 'U', 'D' and 'K' in the figure indicate 'Up', 'Down' and 'Keep' respectively. T_1, T_2, T_3 and T_n show temperature width in which the temperature acquired by the sensor will be categorized. Bayesian networks graphically represent the joint probability distribution of a set of random variables. A Bayesian network is composed of a qualitative portion (its structure) and a quantitative portion (its conditional probabilities). The arcs between nodes represent direct dependencies between the variables. For instance, if the occupant selects the up button, the probability that the temperature in the thermal environment is categorized in T_1 is 0.030 (**Table 1**). This value is calculated considering of the probability distribution U in **Fig.2**. In this paper, probability distributions are defined arbitrary. However, this probability distributions should be made by frequency of actual operation. If there is no data to make the probability distributions, predicted percentage of dissatisfied (PPD)[4] can be used for initializing the distributions.

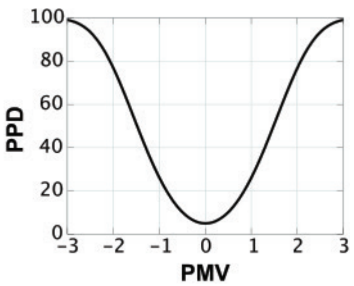

Fig. 3 Predicted percentage of dissatisfied

Table 2 ASHRAE thermal sensation scale

Value	Sensation
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
-1	Slightly cool
-2	Cool
-3	Cold

3 Predicted percentage of dissatisfied (PPD)

Occupants with various clothing levels and performing different activities are in thermal environments with different temperatures, different humidities, and different airflow velocities. The occupants express their thermal comfort level which is often characterized using the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) thermal sensation scale as shown in **Table 2**. The average thermal sensation of a large number of occupants, using the ASHRAE thermal sensation scale, is called the Predicted Mean Vote (PMV). **Figure 3** shows an empirical relationship between the percentages of people dissatisfied (PPD) with PMV defined as follows:

$$\mathrm{PPD} = 100 - 95 \cdot \exp(-0.03353 \cdot \mathrm{PMV}^4 - 0.2179 \cdot \mathrm{PMV}^2) \tag{2}$$

PMV is the predicted mean vote of a large population of people exposed to a certain environment. PMV represents the thermal comfort condition on a scale from -3 to 3 shown in **Table 2**, derived from the physics of heat transfer combined with an empirical fit to sensation. This equation contains terms that relate to clothing insulation I_{cl} [m^{2}K/W], metabolic heat production M [W/m^2], external work W [W/m^2], air temperature T_a [ºC], mean radiant temperature T_r[ºC], relative air speed v [m/s] and vapor pressure of water vapor P[Pa].

$$\begin{aligned}\mathrm{PMV} = \{0.303\exp(-0.036M) + 0.028\}\Big[&(M-W) \\ &-3.05\times10^{-3}\{5733 - 6.99(M-W) - P\} \\ &-0.42\{(M-W) - 58.15\} \\ &-1.7\times10^{-5}M(5867 - P) - 0.0014M(34 - T_a) \\ &-3.96\times10^{-8}f_{cl}\{(T_{cl}+273)^4 - (T_{mrt}+273)^4\} \\ &-f_{cl}h_c(T_{cl} - T_a)\Big]\end{aligned} \tag{3}$$

f_{cl} is the ratio of clothed and nude surface areas given by:

$$
\begin{aligned}
f_{cl} &= 1.0 + 0.2I_{cl} \quad (I_{cl} \leq 0.5) \\
f_{cl} &= 1.05 + 0.1I_{cl} \quad (I_{cl} > 0.5)
\end{aligned} \tag{4}
$$

where T_{cl} is the clothing surface temperature given by repeated calculation of:

$$
\begin{aligned}
T_{cl} &= 35.7 - 0.028(M - W) \\
&\quad -0.155I_{cl}\Big[3.96 \times 10^{-8} f_{cl}\{(T_{cl} + 273)^4 \\
&\quad -(T_{mrt} + 273)^4\} + f_{cl}h_c(T_{cl} - T_a)\Big]
\end{aligned} \tag{5}
$$

where h_c is the heat transfer coefficient,

$$
h_c = \max\{2.38(T_{cl} - T_a)^{0.25}, 12.1\sqrt{v}\} \tag{6}
$$

and T_{mrt} is mean radiant temperature.

4 AC control by predicted request

To predict occupant's request, conditional probabilities $P(U|T_n)$, $P(D|T_n)$ and $P(K|T_n)$ are calculated as follows:

$$
P(U|T_n) = \frac{P(T_n|U)P(U)}{P(T_n)} \tag{7}
$$

where $P(U)$, $P(T_1)$=0.030 due to the **Table 1**. The dominator of the fraction is calculated as follows:

$$
\begin{aligned}
P(T_1) &= P(T_1|U)P(U) + P(T_1|D)P(D) + P(T_1|K)P(K) \\
&= 0.030 \times 0.33 + 0.063 \times 0.33 + 0.180 \times 0.33 \\
&= 0.09009
\end{aligned} \tag{8}
$$

Therefore $P(U|T_1)$ is calculated as 0.1099. In the same way, $P(D|T_1)$ and $P(K|T_1)$ are calculated.

$$
P(D|T_1) = \frac{P(T_1|D)P(D)}{P(T_1)} = 0.2308 \tag{9}
$$

$$
P(K|T_1) = \frac{P(T_1|K)P(K)}{P(T_1)} = 0.6593 \tag{10}
$$

Table 3 Prior probability

Operation	Default frequency (Probability)	Updated frequency(Probability)
Up	10 (10/30=0.33)	12 (12/50=0.24)
Down	10 (10/30=0.33)	20 (20/50=0.40)
Keep	10 (10/30=0.33)	18 (18/50=0.36)

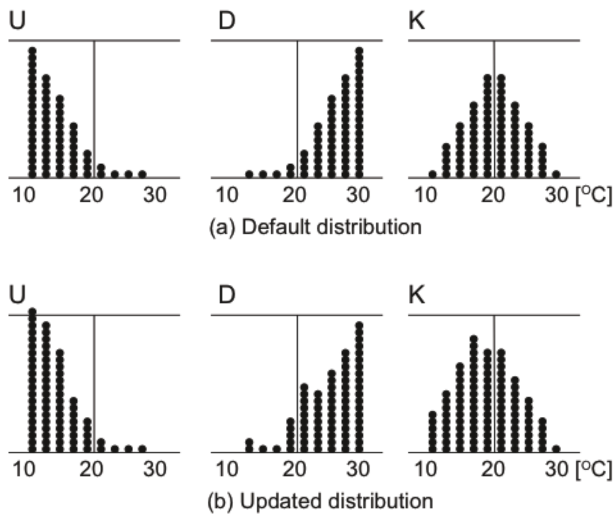

Fig. 4 Update frequency distribution

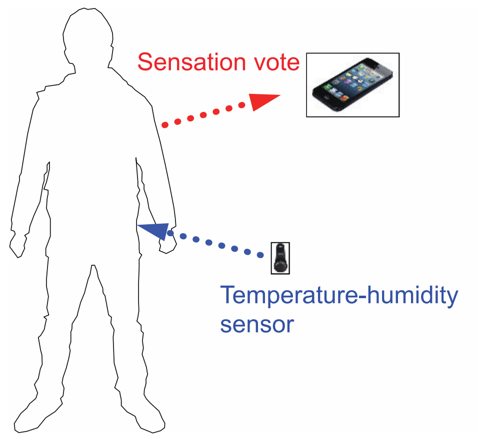

Fig. 5 Temperature-humidity sensor

As a result, following the maximum a posteriori probability (MAP) estimation[5], if $P(U|T_n) < P(D|T_n) < P(K|T_n)$, the occupant's request is predicted as 'Keep.' This request is used for controlling the air conditioning.

5 Update probability distribution

The probability distribution is provided as {Up, Down, Keep}={0.33, 0.33, 0.33} which is defined arbitrary but reasonably as mentioned before. This probability distribution can be made by frequency of actual operation and can be updated dynamically according to occupant's operation. **Table 3** shows an example case of updating the probability distribution. Default frequencies of Up, Down and Keep request is 10, 10 and 10 respectively.

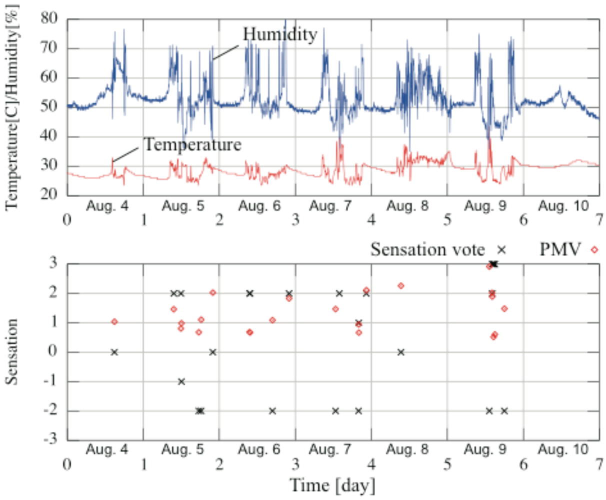

Fig. 6 Sensation vote and PMV (Aug.4 to 10)

After some occupant's operations, frequencies change to 12, 20 and 18 respectively. The probability distribution can be updated to {Up, Down, Keep}={0.24, 0.40, 0.36} in this way. Also the distribution shown in **Fig. 2** can be changed by updating with actual occupant's operations. **Figure 4** shows an example of updating frequency distribution. **Figure 4(a)** correspond to the probability distribution shown in **Fig. 2**. After some operations, the frequency distribution changes to **Fig. 4(b)**.

6 Experiment

6.1 Occupant's sensation vote and PMV

We logged temperature-humidity data in the vicinity of an occupant for a long term. The occupant used a mobile terminal to vote their thermal sensation level at an

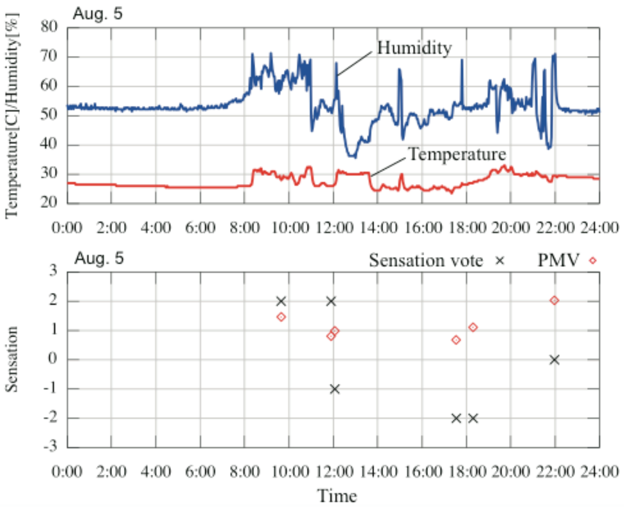

Fig. 7 Sensation vote and PMV (Aug. 5)

arbitrary time during the term (**Fig. 5**). In **Fig. 6**, the

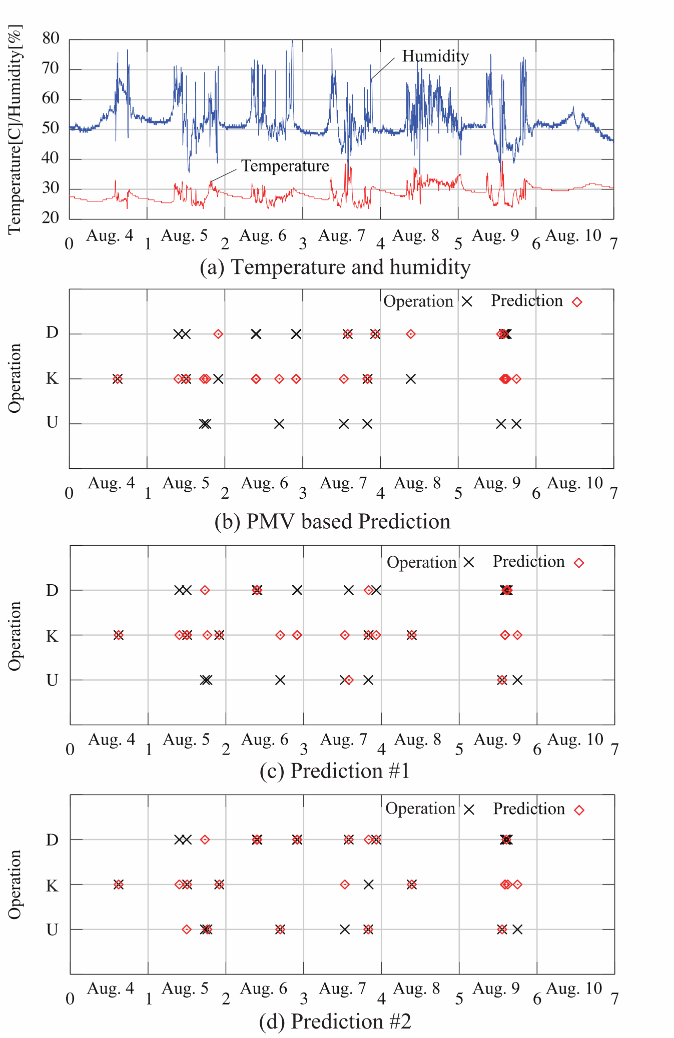

Fig. 8 Prediction results

upper figure shows temperature and humidity change for

7 days on August 4th through 10th. The lower graph compares occupant's sensation vote with PMVs derived from the temperature and humidity. These data change with the cycle of 1 day. **Figure 7** shows the data on Aug. 5th. This result shows not all sensation votes correspond to PMVs. Even the large difference between vote and PMV can be found. Some votes are -2 ('cool') although PMVs indicate 1 ('slightly warm') to 2 ('warm'), for instance. Thus the air-conditioning control based on such index as PMV does not always function sufficiently. Moreover, omitting air-conditioning at that thermal situation are expected to avoid energy waste. For this purpose, it is necessary to predict occupant's sensation correctly even though the difference between vote and PMV arises from individual difference.

6.2 Prediction of occupant's request

Occupant's request is predicted using Bayesian-network-based method mentioned before. In this paper, we assume that occupant's request is directly linked to occupant's vote. 'Hot' and 'Cold' correspond to 'D' and 'U' respectively. However, note that not all sensation votes correspond to thermal indices like PMV.

Figure 8 shows the correlation between the occupant's request and prediction results during the term. **Figure 8(b)** compares occupant's actual requests with PMV-based request predictions. Several predictions are reasonable, however, they do not always correspond to the actual occupant's request. Correct answer rate is 43.4%. **Figure 8(c)** shows the prediction result by using our proposed method mentioned before. In this case, 53.9% of predictions correspond to actual requests. These predictions are derived from only temperature for the sake of simplicity, but human-thermal sensation is affected by other thermal values. Our proposed method could be quite easily extended to multi-sensor use to solve this problem. **Figure 8(d)** shows the prediction result using two sensor values, temperature and humidity. The result shows the best performance, 64.5%, of the three.

6.3 Discussion

The main findings of experiments were as follows. First, conventional thermal indices did not always correspond to actual sensation votes. Because most thermal indices were built for some special static thermal environment. Therefore, not all occupant's votes are predicted by using the indices. Second, our proposed method could predict the occupant's actual sensation vote more precisely than PMV-based prediction using just one sensor value, as probability distribution based on the actual sensation votes was defined. Finally, two-sensor predictions showed the best performance. Our proposed method can easily be applied to multi-sensor system.

7 Conclusion

This paper proposed BN-based air-conditioning controller design considering of occupants requests. To show our basic concept and detailed procedure, the structure of Bayesian networks for this application was described. Then, probability tables which present the probabilistic distribution of occupant's requests at each temperature width were shown. After that, using an example case, we described detailed procedure of our framework. How to predict occupant's requests and how to update probability tables were shown in detail. Finally, we confirmed our proposed method discussing our experimental results. Our method enables to predict how an occupant wants to operate switches on the air-conditioner control panel in certain thermal environment using the Bayesian networks.

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