



**AALBORG UNIVERSITY**  
DENMARK

**Aalborg Universitet**

**CLIMA 2016 - proceedings of the 12th REHVA World Congress**

*volume 8*

Heiselberg, Per Kvols

*Publication date:*  
2016

*Document Version*  
Publisher's PDF, also known as Version of record

[Link to publication from Aalborg University](#)

*Citation for published version (APA):*  
Heiselberg, P. K. (Ed.) (2016). *CLIMA 2016 - proceedings of the 12th REHVA World Congress: volume 8*.  
Department of Civil Engineering, Aalborg University.

**General rights**

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal -

**Take down policy**

If you believe that this document breaches copyright please contact us at [vbn@aub.aau.dk](mailto:vbn@aub.aau.dk) providing details, and we will remove access to the work immediately and investigate your claim.

# Estimation of Comfortable Room Temperature by Survival Analysis

Ryosuke Takeuchi<sup>#1</sup>, Shuichiro Imahara<sup>#2</sup>, Toru Yano<sup>#3</sup>

<sup>#</sup>Corporate Research & Development Center, Toshiba Corporation  
1, Komukai-Toshiba-cho, Saiwai-ku, Kawasaki, Japan

<sup>1</sup>ryosuke.takeuchi@toshiba.co.jp

<sup>2</sup>shuuichiro.imahara@toshiba.co.jp

<sup>3</sup>toru1.yano@toshiba.co.jp

## Abstract

*In the Lyon smart community project developed by Toshiba, we provide energy-saving functions controlling preset temperature of thermostats that operate valves. This paper proposes a method of changing the thermostat preset temperature by estimating the residents' comfortable room temperature from data of motion sensors and thermometers. The proposed method regards duration of a temperature as a survival time and estimates a resident's comfortable temperature by survival analysis because the duration of the temperature is shorter when the resident feels cold. The method consists of a training phase and an operating phase. In the training phase, regarding rise in temperature as resident's discomfort while the resident is in the room, the method obtains a Weibull distribution per temperature from the durations of each temperature. Regarding their parameters as explanatory variables and degrees of comfort obtained in advance as objective variables, the method builds a classifier. In the operating phase, there are two cases: finding the lowest comfortable temperature and the multiple lowest comfortable temperatures corresponding to multiple residents. In the former case, the method obtains one Weibull distribution. In the latter case, it obtains Weibull mixture distributions. We evaluated the method, using the data in four living rooms in Japan during five winter months. In the former case, we confirmed that the estimated comfortable temperatures in winter approximately coincide with the result of a survey of the residents. The method contributes 24.0% energy saving in heating. In the latter case, it may save more 4.4% energy than the former case.*

**Keywords - HEMS; Survival Analysis; Weibull Distribution; Weibull Mixture Distribution; Comfortable room temperature Estimation; Lyon smart community project;**

## 1. Introduction

In the smart community project developed by Toshiba in Lyon, we introduce a Home Energy Management System (HEMS) to achieve energy saving and comfort [1]. The HEMS provides energy-saving functions that not only visualize energy consumption but also control preset temperature of

thermostats that operate valves by feedback control. The HEMS's main target is energy saving for heating that accounts for 69% of resident's total energy consumption in France [2]. Since energy consumption of heating tends to be high when preset temperature is high, it is preferable that the preset temperature is set as low as possible without compromising comfort.

Murakami et al. [3] proposed a method whereby occupants' requests are collected from their personal computers and reflected in control of an air-conditioning system for offices. It is, however, troublesome for occupants to input their comfortable room temperatures and for developers to develop an input system on a HEMS. Moreover, when the occupants request the current preset temperature as the comfortable temperature, there may be a difference between the comfortable temperature requested by occupants and their actual comfortable temperature. That may induce loss of energy saving. PMV (Predicted Mean Vote) is a popular indicator of thermal comfort in homes and offices. Yamada et al. [4] used PMV to operate a heating system that ensures comfort. However, since it is necessary for calculation of PMV to measure air speed and radiant temperature, this approach needs new devices in a room and raises costs. Therefore, this approach is unsuitable for our HEMS. It is preferable to estimate the resident's comfortable temperature without an additional user-input system or a special measuring instrument. This paper proposes a method of changing the thermostat preset temperature by estimating the resident's comfortable temperature from data of motion sensors and thermometers.

## **2. Estimation of Comfortable Room Temperature**

Generally, a resident may change heating preset temperature and a room temperature rises when the resident feels cold. On the other hand, the room temperature may remain unchanged when the resident feels comfortable. We propose a method that regards the duration of a temperature as a survival time, builds a model from survival times by survival analysis, a statistical technique, and estimates the resident's comfortable temperature with the model's features (Fig. 1). The principal characteristic of the proposed method is that the resident's comfortable temperature is estimated only from data of motion sensors and thermostats.

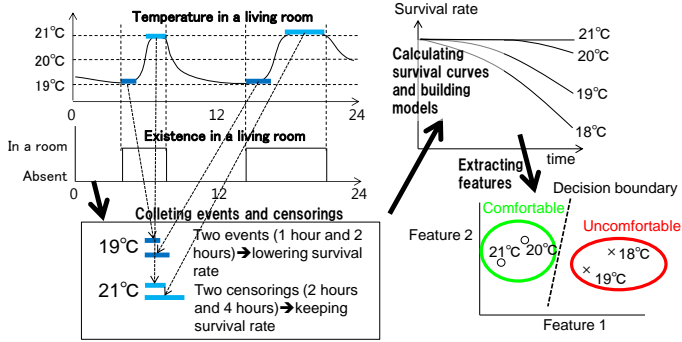


Fig. 1 Outline of our proposed method

### 3. Method

In survival analysis, there are two kinds of ends of survival times: one is an “event” and the other is a “censoring”<sup>1</sup>. We define the event as a rise in room temperature while a resident is in a room. In addition, we define the censoring as a fall in temperature while the resident is in the room, the resident’s outgo from the room and passing of a fixed time during the resident’s stay in this paper. A set of the survival times with events and censorings are called survival data.

The proposed method consists of a training phase and an operating phase. In the training phase the method models the survival data by a parametric model [1]. Then the method extracts features from the models and combines them with the correct comfortable temperatures that are obtained, for instance, by a questionnaire. Finally, the method builds a classifier from the combined data.

In the operating phase, the method also collects survival data and extracts features. Then the method classifies each temperature as comfortable or not with the built classifier. The lowest comfortable temperature is set as the preset heating temperature.

First, we illustrate the training phase consisting of 3 steps: (Step 1) preparing survival data, (Step 2) extracting features and (Step 3) building a classifier.

#### (Step 1) Preparing survival data

The method assesses whether a resident is in a room or not per minute from motion sensors. We call the assessed data in-room data. It also obtains room temperature from a thermometer within a thermostat. We collect survival data of temperatures from in-room data and temperature data (Fig. 2).

<sup>1</sup> An event is originally defined as a death of a patient and a censoring is as some exclusion of a patient in medical research.

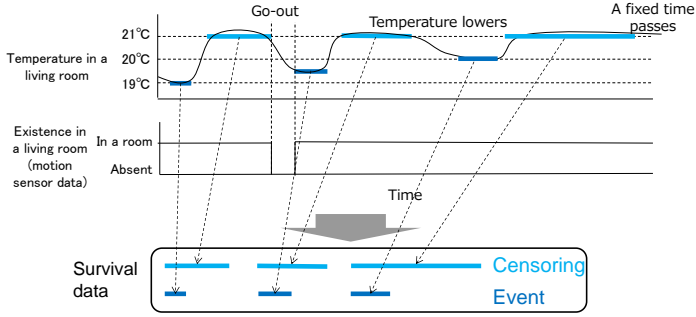


Fig. 2 (Step 1) Preparing survival data

### (Step 2) Extracting features

By fitting survival data of each temperature to the Weibull distribution, the method regards the Weibull distribution's parameters as features. Before explaining Weibull distribution, we explain some definitions for preparation.  $T$  is a non-minus random variable and means time by which an event is observed. A survival function  $F$  is defined using  $T$  as

$$F(t) = P(T > t), 0 < t < \infty. \quad (1)$$

$F(t)$  means a probability that no event is observed by time  $t$ . A survival function of Weibull distribution is defined as

$$F(t) = \exp[-(\lambda t)^p], \lambda, p > 0, \quad (2)$$

where  $\lambda$  is a scale parameter and  $p$  is a shape parameter. In the method,  $\lambda$  and  $p$  are features.

Fig. 3 is an example of calculated Weibull distributions of temperatures in a room. The vertical line shows survival rate [%] and horizontal one survival time [minute]. Each curve is each temperature's Weibull distribution. According to the result of a questionnaire, we categorize these curves into comfortable and uncomfortable by line types: a solid curve is a comfortable temperature and a dashed one is uncomfortable one. Survival rates of higher temperatures tend to remain.

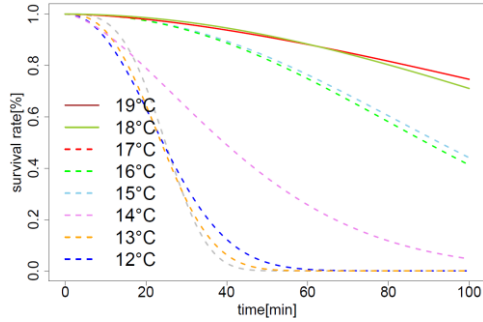


Fig. 3 Example of Weibull distribution of each room temperature

### (Step 3) Building a classifier

By setting  $\lambda$ s and  $p$ s of all room temperatures as explanatory variables and corresponding degrees of comfort as objective variables, the method builds a model of a support vector machine (SVM), a supervised learning model, and uses the built model as a classifier. This SVM calculates a probability that a feature point ( $\lambda$ ,  $p$ ) is comfortable. When the probability of a temperature exceeds a decision boundary with a fixed probability value, the temperature is estimated as comfort.

In order to obtain a decision boundary, we use two evaluation indices: an energy-saving estimate and a rate of uncomfortable rooms. The energy-saving estimate indicates how much energy may be saved per room and is calculated as a product of the following values:

- \*The difference between the average heating preset temperature (22°C in Japan, according to Toshiba's questionnaire) and the estimated lowest comfortable room temperature.

- \*How much energy may be saved at most when heating preset temperature is lowered 1°C (10% in Japan [5]).

- \*The rate of energy consumption of heating in a house (25% in Japan and 69% in France [2]).

The rate of uncomfortable rooms indicates the rate of rooms where the estimated lowest comfortable temperature is actually uncomfortable for its residents. As an illustration, if the estimated lowest comfortable temperatures in three rooms are comfortable and the other one in the other room is uncomfortable, the rate of uncomfortable rooms is 25%.

In the operating phase, there are two ways. In order to find the lowest comfortable room temperature, the method collects survival data and extracts features from the Weibull distribution of each temperature as well as the training phase. The features are only one pair for each temperature. Then the method classifies each temperature as comfortable or not with the built classifier. The lowest comfortable temperature is set as the preset heating temperature.

On the other hand, when some residents are sensitive to cold and others are sensitive to heat in the same room, the method can find some pairs of features for each temperature using Weibull mixture distributions [6]. The Weibull mixture distributions are distribution of weighted sum of some Weibull distributions. Survival function of Weibull mixture distributions is defined by

$$F(t|k, \mathbf{w}, \boldsymbol{\lambda}, \mathbf{p}) = \sum_{j=1}^k w_j \exp[-(\lambda_j t)^{p_j}], \quad (3)$$

where  $\boldsymbol{\theta} = (\theta_1, \dots, \theta_k)$  and  $\mathbf{p} = (p_1, \dots, p_k)$  are the parameters of each Weibull distribution.  $\mathbf{w} = (w_1, \dots, w_k)$  is a vector of weights whose elements are non-negative and sum to 1.

We use Markov chain Monte Carlo methods (MCMC) [6] that repeat parameter sampling to infer the parameters. We assume the presence of only two kinds of residents in a room: one is sensitive to cold and the other is sensitive to heat. Therefore we assume  $k = 2$ . In this case, the method calculates features by the following two steps.

(1) Simulate 10000 steps of MCMC. Calculate means of  $\lambda$ s and  $p$ s from 5000 steps where parameters may become stable. Besides, remove the highest 5% of  $\lambda$ s and  $p$ s because means are affected by such  $\lambda$ s and  $p$ s.

(2) Try (1) some times. Calculate means of  $\lambda$ s and  $p$ s in (1) and regard them as features.

Next, the method classifies each temperature using the calculated features and the classifier obtained in the training phase.

#### 4. Experiment

We evaluated the method for heating, using the data in living rooms of four apartments in Tokyo and its suburbs in Japan during five months in winter. The areas of the living rooms ranged from 10 to 36m<sup>2</sup>. Heating systems in the living rooms were air conditioners which didn't lead thermal stratification. The temperature decay per hour in each living room was 0.7°C at most when the air conditioners didn't work at midnight. The heating system was intermittent because residents turned it off when leaving the living room. We had set motion sensors and temperature sensors measuring by 0.1°C in the living rooms. The data in this experiment was for December 2012 – February 2013 and for December 2013 - January 2014. From motion sensor data, we assessed whether a resident is in a room or not per minute. Then we collected survival data from in-room data and room temperature data. We removed survival data of temperatures that have less than 10 sample points because Weibull distributions calculated from such samples points were not reliable. We extracted features from the survival data. Then we combined the features and comfort of each temperature obtained by a questionnaire survey of the residents and built a classifier with the data of

one of the five months. We evaluated values of the two introduced indices by applying the classifier to the data of the other four months. By repeating this procedure every month, we calculated the means of two indices with respect to the whole months, respectively. We determined the decision boundary from the means.

We also evaluated whether, using the above data, the method can separate features' pairs of a room where one person is sensitive to cold and the other is sensitive to heat.

## 5. Result

The room temperature among all households ranged from 10 to 27 °C. We analyze data of these temperatures.

First, we mention the training phase. As an example of the result, classifiers built with one-month data of December 2012 determine comfort of each temperature from the features of December 2013 in Fig. 4 whose vertical line shows a shape parameter  $p$  and whose horizontal one a scale parameter  $\lambda$ . Circles are comfortable temperatures and crosses are uncomfortable temperatures. They are plotted along with features calculated from the survival data. The labels of each mark are rooms' ID and temperature. Lines are decision boundaries [%]. The smaller decision boundaries tend to classify a temperature as comfort. By selecting a valid decision boundary, the method can correctly classify most temperatures.

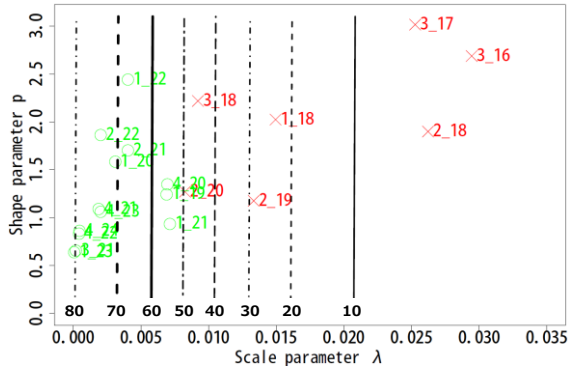


Fig. 4 Example of features and decision boundaries

Fig. 5 plots the means of the two introduced indices on each decision boundary are used in the training phase. In the cases that the decision boundaries of 40% and 50% are used, the rates of uncomfortable rooms are respectively 50.8% and 43.8%. It means residents often feel uncomfortable. In the case that the decision boundary of 70% is used, the energy-saving estimate is 3.9% (15.6% when it comes to heating energy). In the case that the decision boundary of 60% is used, the energy-saving estimate is 5.8% (24.0%) and the rate of uncomfortable rooms is 25.6%. It balances well. The amount of energy consumption of heating in an average house in Japan is



10GJ per year<sup>2</sup>, therefore energy-saving amount of heating is 2.4GJ per year [2]. While the rate of uncomfortable rooms given by the decision boundary of 70% is less than that given by the decision boundary of 60%, the 60%-decision boundary saves more energy.

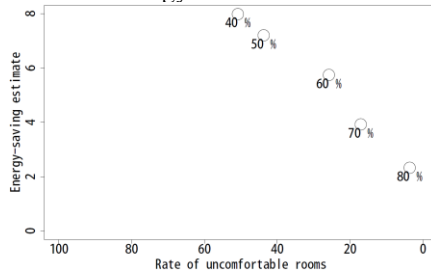


Fig. 5 Means of the two indices on each decision boundaries in the training phase

Second, we mention a case in which some residents are in the same room. Fig. 6 consists of plots of features at 16°C, 17°C and 18°C. As in Fig. 4, its vertical line shows a shape parameter  $p$  and its horizontal one a scale parameter  $\lambda$ . A black triangle is a feature point calculated from the Weibull distribution whose  $w$  is larger, and a red outlined triangle is one calculated from the Weibull distribution whose  $w$  is smaller. A solid line is the decision boundary built with data in the four living rooms in December 2012 at 60%, because it balanced well in the training phase. At 16°C, both the black triangle and the red outlined one are plotted to the right of the decision boundary. It means the both are estimated as discomfort. At 17°C, the triangles are separated by a decision boundary. It means 17°C is uncomfortable for a resident who tends to feel cold and comfortable for the other resident who tends to feel hot. At 18°C, both the black triangle and the red outlined one are estimated as comfort. The resident in this room stated that each resident turned on heating at a different temperature. This fact supported the method's estimation.

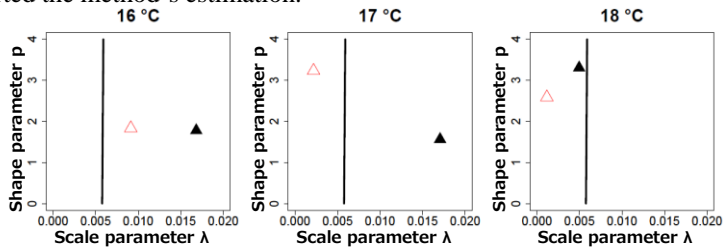


Fig. 6 Features at each temperature in case some resident are in a room

On the other hand, when the method supposed some lowest comfortable temperatures, the method estimated 18°C as the lowest comfortable temperature from the first Weibull distribution whose weight was 50% and

<sup>2</sup> In France 44GJ per year [2].

from the second one whose weight was also 50% it estimated 17°C. When the method found only one lowest comfortable temperature, the lowest comfortable temperature of the household was 18°C. By setting the preset temperature of the thermostat to 18°C, the energy-saving estimate of the room was given by

$$(22.0^{\circ}\text{C} - 18.0^{\circ}\text{C}) \times 10\% \times 25\% = 10.0\%.$$

Assuming that we can set the preset temperature to 18°C and 17°C in proportion to the weights of the Weibull distributions, the energy-saving estimate of the room was given by

$$\begin{aligned} & ((22.0^{\circ}\text{C} - 17.0^{\circ}\text{C}) \times 50\%) + (22.0^{\circ}\text{C} - 18.0^{\circ}\text{C}) \times 50\% \times 10\% \times 25\% \\ & = 11.1\%. \end{aligned}$$

Therefore, the energy-saving estimate was raised 1.1% (4.4% when it comes to heating energy) and use of the Weibull mixture distributions contributed to greater energy saving.

## 6. Discussion

As we expected, uncomfortable temperatures' durations are shorter and comfortable temperatures' durations are longer although comfortable temperatures are different among rooms. The method can classify comfortable and uncomfortable temperatures using Weibull distributions' parameters as features. By introducing the two indices introduced, namely, the energy-saving estimate and the rate of uncomfortable rooms, we can determine a well-balanced decision boundary.

We have confirmed that the proposed method can estimate the lowest comfortable temperature. According to the questionnaires we had distributed to 400 households in France, almost half of the residents had changed the heating settings less than once a month. Besides, the results also said 63.8% of the French residents had accepted automatic change of heating settings. Therefore, French people will probably accept the proposed method.

The data in this paper has been collected in Tokyo and its suburbs in Japan. Generally, a resident in this area usually turns off the heating system when leaving a room as long as the resident does not forget to do so. Therefore, when the resident returns to the room, its temperature is sufficiently low for the resident to feel cold and turn on the heating. Thus the proposed method can estimate whether the temperature is uncomfortable or not. In northern Japan and France, some residents do not turn off the heating even when they go out. Since the room temperatures are unchanged, we need to automatically lower room temperature to get more sample points and estimate the actual lowest comfortable temperature.

## 7. Conclusion

In the Lyon smart community project, our HEMS estimates comfortable room temperature in each room and recommends a suitable preset heating temperature to each resident. The proposed method estimates residents'

comfortable room temperature from its temperature data, where residents are in the room, by applying a Weibull distribution to durations of each temperature and classifying comfort or not with respect to the parameters of the Weibull distribution as features. For obtaining a decision boundary, we have introduced the two indices: the energy-saving estimate, which indicates how much energy is saved in each room, and the rate of uncomfortable rooms, which indicates the rate of rooms where the estimated lowest comfortable temperature is actually uncomfortable for residents. We have evaluated the method for heating, using the data of four living rooms in Japan during five winter months. We have confirmed that the estimated comfortable temperatures in winter approximately coincide with the result of a survey of the residents. The energy-saving estimate is 24.0%.

### **Acknowledgment**

Funding from New Energy and Industrial Technology Development Organization (NEDO) is gratefully acknowledged.

### **References**

- [1] Ryosuke Takeuchi, Toru Yano and Shuichiro Imahara. Estimation of comfortable room temperature by survival analysis in NEDO Lyon Project HEMS. IRED2014, pp. 170-171, Kyoto, 17-21 November 2014. NEDO.
- [2] Hidetoshi Nakagami. Energy demand and problems in household. [online] [http://www.pref.fukuoka.lg.jp/uploaded/life/79652\\_16830141\\_misc.pdf](http://www.pref.fukuoka.lg.jp/uploaded/life/79652_16830141_misc.pdf) [Accessed 14 September 2015] (in Japanese).
- [3] Yoshifumi Murakami, Masaaki Terano, Kana Mizutani, Masayuki Harada and Satoru Kuno. Field experiments on energy consumption and thermal comfort in the office environment controlled by occupants' requirements from PC terminal. *Building and Environment*. 42 (2007) 4022-4027.
- [4] F. Yamada, K. Yonezawa, S. Sugawara, and N. Nishimura. Development of Energy-saving Air-Conditioning Control System for Office Building based on Comfort Index, *IEEJ Trans. IA*, Vol. 119, No.11 (1999), pp. 1377-1385 (in Japanese).
- [5] Daikin, Relationship between effective temperature and humidity. [online]<http://www.daikin.co.jp/csr/information/select/04.html> [Accessed 14 September 2015] (in Japanese).
- [6] J.M. Marín, M.R. Rodríguez Bernal, Michael P. Wiper. Using Weibull Mixture Distributions To Model Heterogeneous Survival Data. *Communication in Statistics: Simulation and Computation*. Volume 34, Issue 3, (2005), pp. 673-684