Available online at www.sciencedirect.com
ScienceDirect
Applied Thermal Engineering 28 (2008) 1906–1917
APPLIED THERMAL ENGINEERING
www.elsevier.com/locate/apthermeng

Controlling automobile thermal comfort using optimized fuzzy controller

Yadollah Farzaneh, Ali A. Tootoonchi *

Department of Mechanical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

Received 31 January 2007; accepted 5 December 2007
Available online 26 January 2008

Abstract

Providing thermal comfort and saving energy are two main goals of heating, ventilation and air conditioning (HVAC) systems. A controller with temperature feedback cannot best achieve the thermal comfort. This is because thermal comfort is influenced by many variables such as, temperature, relative humidity, air velocity, environment radiation, activity level and cloths insulation. In this study Fanger's predicted mean value (PMV) index is used as controller feedback. It is simplified without introducing significant error. Thermal models of the cabin and HVAC system are developed. Evaporator cooling capacity is selected as a criterion for energy consumption. Two fuzzy controllers one with temperature as its feedback and the other PMV index as its feedback are designed. Results show that the PMV feedback controller better controls the thermal comfort and energy consumption than the system with temperature feedback. Next, the parameters of the fuzzy controller are optimized by genetic algorithm. Results indicate that thermal comfort level is further increased while energy consumption is decreased. Finally, robustness analysis is performed which shows the robustness of optimized controller to variables variations.

Keywords: Thermal comfort; PMV; Automobile cabin; Fuzzy controller; Energy; Genetic algorithm; Robustness analysis

1. Introduction

Temperature in an automobile cabin is an important factor in the occurrence of traffic accidents [1]. Zlatoper investigated the influence of 10 factors on traffic accident in Unites States and observed that temperature rated third [2]. A better climate control system in an automobile improves thermal comfort which results in increased driver caution and thus improves driving performance and safety in different driving conditions. Behr Company's researches show air conditioning system is one of the most important comfort equipment in automobiles which is why most automobiles today are equipped with it [3]. Performance improvement of an AC system in automobile requires careful analysis of the air conditioning components. An optimum system should maintain thermal comfort under time varying thermal loads while minimizing energy consumption.

Compressor used in a cooling system is driven by automobile engine and therefore increases the fuel consumption. Studies in this area show that the mechanical compressor can increase fuel used in automobile by about 12–17% for subcompact to mid-size automobiles [4].

Control system is a key factor for improving the performance of automobile air conditioning. Manual control requires skill and experience about system. During travel, driver is focused on driving task and in most condition he/she is unaware of complex combination of temperature and climate changes, so he/she may not be able to react to changes. Automatic control frees the driver from this task. Daanen et al. [1] in 2003 investigated the influence of driving performance in several climate conditions. They concluded that a thermo neutral temperature in a car

* Corresponding author. Tel.: +98 511 8815100.
E-mail address: ali_akbarzadeh_t@yahoo.com (A.A. Tootoonchi).

1359-4311/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.applthermaleng.2007.12.025

Nomenclature

bp	blower power (kW)
C	thermal capacity, $\dot{m}Cp$ (kW/°C)
COP	coefficient of performance
Cp	specific heat (kJ/kg °C)
$\dot{E}$	rate of change of energy (kW)
ff	fitness function
$\dot{Q}$	rate of heat transfer (kW)
m	mass (kg)
$\dot{m}$	mass flow rate (kg/s)
NTU	number of transfer units
pf	percent of fresh air
ptd	position of temperature door
T	temperature (°C)
V	velocity (m/s)
$\dot{W}$	power (kW)
ε	heat exchanger effectiveness

Subscripts

a	air
amb	ambient
b	blower
c	cold
cabin	automobile cabin
cooler	cooler compartment
e	evaporator
eR	evaporator refrigerant
fa	fresh air
gen	generation
H	heater core
h	hot
i	in
min	minimum
o	out
R	refrigerant
ra	re-circulation air
w	water

enhances driving performance and may thus positively affect safety.

Tabe et al. [5] used modern control theory and derived the mathematical model using statistical identification method. Because the system is complex with continuously varying parameters more researchers have preferred to use intelligent and more advanced control methods. Davis et al. [6] used fuzzy logic control system to address the inherently nonlinearity of AC components and to allow the control to be expressed in the same heuristic terms that an occupant would use in describing the level of comfort. Wei [7] developed an intelligent automotive climate control system based on human-sensory response. Intelligent methods can be combined with traditional methods to improve control system efficiency. Zhong et al. [8] designed two controllers for controlling the indoor air temperature of a car, the general fuzzy controller and the state feedback with weighting fuzzy controller. By comparing the results of the two experiments, they showed that the state feedback with weighting fuzzy controller is more efficient than the other in controlling the automobile indoor air temperature. Durovic [9] used Artificial Neural Network under different climate conditions for automotive climate control.

In most articles, temperature feedback is used to indicate thermal comfort. However, the temperature alone cannot explain thermal comfort correctly and it should be combined with other factors to better indicate thermal comfort.

The fundamental goal of this paper is to make automobile compartments a more comfortable thermal environment while minimizing energy consumption. Thermal modeling of Peugeot 206 automobile cabin is performed to identify the effect of control parameters on thermal response. PMV index is used to show thermal comfort and its variables are simplified. With this simplification, if the inside cabin temperature and air velocity are known, a good prediction of comfort can be obtained. Two fuzzy controllers with temperature feedback and PMV feedback are designed. An index for energy consumption is also suggested. It is shown that controller with PMV feedback is more effective than controller with temperature feedback. The PMV controller also better minimizes the energy consumption. Finally, the membership functions of fuzzy controller are tuned by genetic algorithm to further improve the performance of fuzzy controller. After optimization, robustness analysis is performed to show the robustness of optimized controller to variation in model variables.

2. Thermal modeling of automobile cabin

In this section, mathematical model of thermal environment for an automobile cabin is derived. Specific parameters for Peugeot 206 automobile are used. This model includes blower, evaporator, heater core as well as the impact of important thermal loads such as sun radiation, outside air temperature and passengers on climate control of cabin. A schematic model of system is shown in Fig. 1.

Mathematical modeling should be performed in a manner to clearly show the effect of control parameters on occupant thermal comfort. The main control variables are blower power and the position of temperature door. The first variable regulates the blower speed and the second regulates the necessary blend of hot and cold air.

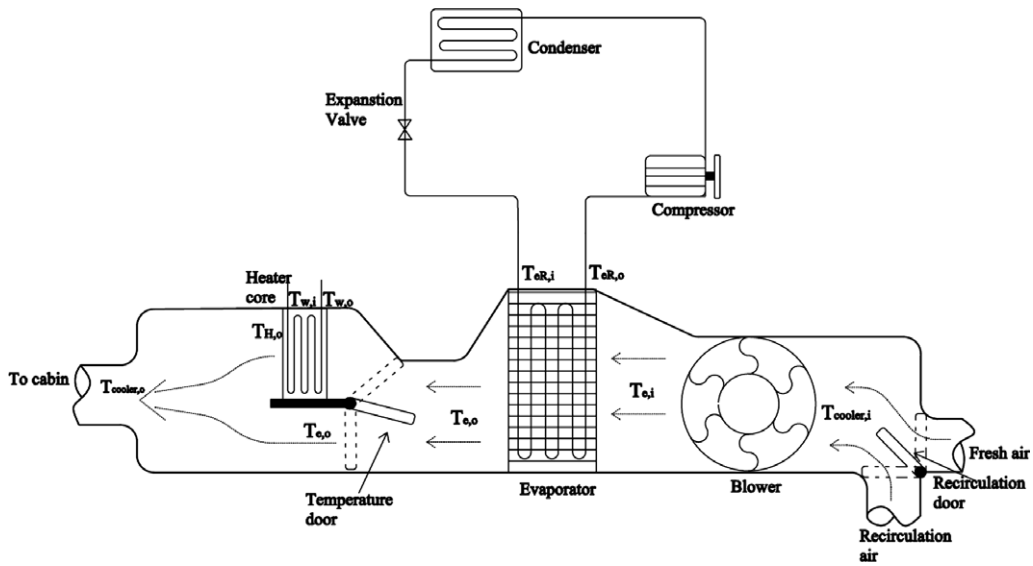

Fig. 1. schematic of automobile cabin and air conditioning systems.

2.1. Assumptions

The following assumptions were made to derive the mathematical model:

- Dry air.
- Ideal gas behavior.
- Perfect air mixing.
- Neglect potential energy in all parts.
- Neglect thermal losses between components.
- Negligible infiltration and exfiltration effects.
- Neglect transient effect in components and channels.
- Negligible energy storage in air conditioning components.
- Zero mechanical work in the cabin ($\dot{W}_{\text{cabin}} = 0$).
- Air parameters at standard conditions of 20 °C, 50% rh, sea level.
- Air parameter exiting the cabin have the same properties as inside the cabin.

Above assumptions help to simplify the equations while produce negligible error in modeling.

2.2. Thermal loads model

An automobile moves in highly transient conditions and its thermal loads depend on many variables, such as sun radiation, interior surface radiation, temperature difference between cabin and ambient, heat from moving parts, combustion heat, human thermal load and fresh air entering the cabin. Many works are performed for calculation of thermal loads in automobile [10,11]. The derived equations are usually function of many parameters and are complex to calculate. For the control purpose it is simpler to estimate the important loads by either sensors or empirical equations. In this article, the thermal loads generated by solar radiation, outside air and cabin temperature difference as well as assumption of four people in cabin is estimated by an empirical formula for Peugeot 206 automobile suggested by [12].

$$\dot{E}_{\text{gen}} = 0.118(T_{\text{amb}} - T_{\text{cabin}}) + 0.0022(T_{\text{amb}} - T_{\text{cabin}}) + 0.2618. \quad (1)$$

2.3. Blower model

Blower is an important component in achieving comfort, thus one of the controlling parameter is blower power. Temperature difference before and after blower is not significant and therefore thermal loss is negligible.

Relation between blower power, air velocity and air flow rate must be known for the blower. These relations are derived experimentally for Peugeot 206 automobile. Air velocity meter, model DO2003 with probe AP471S from Delta OHM was used. Two experiments were performed.

Experiment 1: Four front dashboard air inlets were opened while all other air inlets were kept closed. To ensure comfort for the passengers in the back seat the four inlets were pointed directly towards back seats. Air velocity at different power setting was measured near the driver head. This measurement was repeated several times and the average was recorded. Blower power was normalized based on its maximum value. Fig. 2 shows the results.

Experiment 2: In order to reduce experiment error, a second experiment was performed to obtain air velocity at the dashboard air inlets. Two central dashboard air inlets were opened while all others were kept closed. Air velocity as well as inlet section area were measured. Therefore the relation between air flow rate and blower power can be determined (Fig. 3).

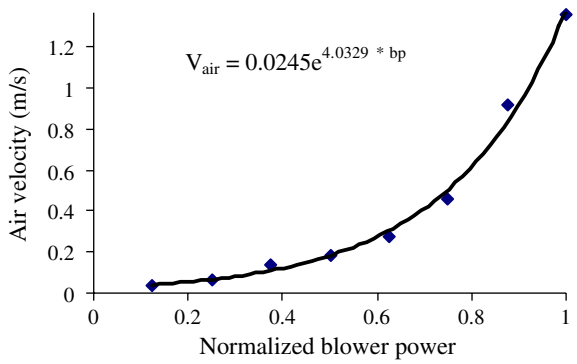

Fig. 2. Mean air velocity versus blower speed.

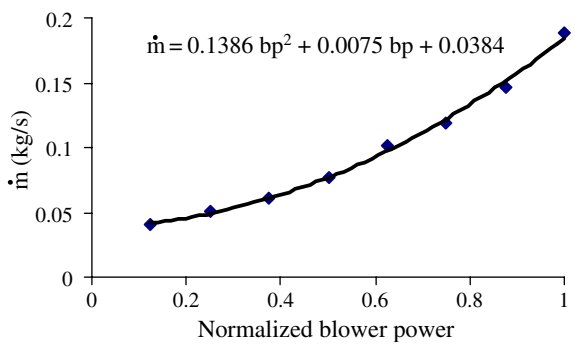

Fig. 3. Mass flow rate versus blower speed.

2.4. Heat exchangers model

Evaporator is cooled through the flow of refrigerant. Heater core is heated through the flow of hot water from engine. Although these two heat exchangers have different tasks, they are similar from the modeling point of view. Energy equilibrium on air side and working fluid side give the heat transfer equations. Heat transfer coefficients are the most important parameters that should be known for energy equilibrium equations. Many researches have been performed in this area [13,14]. Energy equilibrium equations and ε-NTU procedure are usually used for design and analysis of heat exchangers. ε-NTU procedure leads to calculation of heat exchanger effectiveness. However, for simplicity heat exchangers effectiveness value for Peugeot 206 automobile is used from [12]. Heat exchanger effectiveness [15] is defined as

$$\varepsilon = \frac{Q_{\text{actual}}}{Q_{\max}} = \frac{Q_{\text{actual}}}{C_{\min}(T_{\text{hot,i}} - T_{\text{cold,i}})}. \tag{2}$$

Exhaust air temperature from the heat exchangers is the desired value in this study. It can be found by expanding Eq. (2). For the evaporator and heater core these temperatures are explained by the following equations:

$$T_{\text{e,o}} = T_{\text{e,i}} - \frac{\varepsilon_{\text{e}} C_{\min,\text{e}}}{\dot{m}_{\text{air}} Cp_{\text{a}}}(T_{\text{e,i}} - T_{\text{eR,i}}), \tag{3}$$

$$T_{\text{H,o}} = T_{\text{H,i}} + \frac{\varepsilon_{\text{H}} C_{\min,\text{H}}}{\dot{m}_{\text{air}} Cp_{\text{a}}}(T_{\text{w,i}} - T_{\text{H,i}}). \tag{4}$$

The position of temperature door is the other controlling parameter. This position specifies the necessary blend of hot and cold air (Fig. 1). It is indicated by ptd (position of temperature door) coefficient and is normalized to (0, 1). Applying energy equilibrium after temperature door, the air temperature that enters the cabin is calculated by:

$$T_{\text{cooler,o}} = \text{ptd} \cdot T_{\text{e,o}} + (1 - \text{ptd}) T_{\text{H,o}}. \tag{5}$$

2.5. Overall model of the system

The principle of energy and mass conservation from thermodynamics are used to model the system. Overall model of the system is derived to show the air temperature and velocity in the cabin. The effect of control parameters is also included in the model

$$\frac{\mathrm{d}E_{\text{cabin}}}{\mathrm{d}t} = \dot{E}_{\text{gen}} - \dot{W}_{\text{cabin}} + \sum \dot{E}_{\text{cabin,i}} - \sum \dot{E}_{\text{cabin,o}}, \tag{6}$$

$$\frac{\mathrm{d}m_{\text{cabin}}}{\mathrm{d}t} = \sum \dot{m}_{\text{in}} - \sum \dot{m}_{\text{out}} = 0 \Rightarrow m_{\text{cabin}} = \text{const.} \tag{7}$$

Variables used in Eq. (6) are simplified as follows:

$$\frac{\mathrm{d}E_{\text{cabin}}}{\mathrm{d}t} = \frac{\mathrm{d}(m_{\text{cabin}} h_{\text{cabin}})}{\mathrm{d}t} = \frac{\mathrm{d}}{\mathrm{d}t}[(\rho_{\text{air}} V_{\text{cabin}})(CpT_{\text{cabin}})] = \rho_{\text{air}} V_{\text{cabin}} Cp \frac{\mathrm{d}T_{\text{cabin}}}{\mathrm{d}t}, \tag{8}$$

$$\sum \dot{E}_{\text{cabin,i}} = \dot{E}_{\text{cooler,o}} = \dot{m}_{\text{air}} CpT_{\text{cooler,o}}, \tag{9}$$

$$\sum \dot{E}_{\text{cabin,o}} = \dot{E}_{\text{cooler,i}} = \dot{m}_{\text{air}} CpT_{\text{cabin}}. \tag{10}$$

Eqs. (1), (8)–(10) are placed into Eq. (6) which leads to

$$A \cdot \dot{T}_{\text{cabin}} + B \cdot T_{\text{cabin}} = C \cdot T_{\text{amb}} + D \cdot T_{\text{eR,i}} + E \cdot T_{\text{w,i}} + F, \tag{11}$$

$$\begin{aligned}
A &= \rho_{\text{air}} V_{\text{cabin}} \dot{m}_{\text{air}} Cp_{\text{a}}^2, \\
B &= \dot{m}_{\text{air}} Cp_{\text{a}} \{\dot{m}_{\text{air}} Cp_{\text{a}} - (1 - \text{pf})(1 - \varepsilon_{\text{e}})[\dot{m}_{\text{air}} Cp_{\text{a}} \\
&\quad + (1 - \text{ptd})\varepsilon_{\text{H}} C_{\min,\text{H}}] + 0.1202\}, \\
C &= pf(1 - \varepsilon_{\text{e}})\dot{m}_{\text{air}} Cp_{\text{a}}[\dot{m}_{\text{air}} Cp_{\text{a}} + (1 - \text{ptd})\varepsilon_{\text{H}} C_{\min,\text{H}}] \\
&\quad + \dot{m}_{\text{air}} Cp_{\text{a}} 0.1202, \\
D &= \dot{m}_{\text{air}} Cp_{\text{a}} \varepsilon_{\text{e}}[\dot{m}_{\text{air}} Cp_{\text{a}} \text{ptd} + (1 - \text{ptd})(\dot{m}_{\text{air}} Cp_{\text{a}} + \varepsilon_{\text{H}} C_{\min,\text{H}})], \\
E &= -\varepsilon_{\text{e}}[\dot{m}_{\text{air}} Cp_{\text{a}} \text{ptd} + (1 - \text{ptd})(\dot{m}_{\text{air}} Cp_{\text{a}} + \varepsilon_{\text{H}} C_{\min,\text{H}})] \\
&\quad \times (1 - \text{ptd})\varepsilon_{\text{H}} C_{\min,\text{H}}, \\
F &= \dot{m}_{\text{air}} Cp_{\text{a}} 0.2618, \\
V_{\text{air}} &= 0.0245 \exp(4.0329 * \text{bp}).
\end{aligned} \tag{12}$$

Governing equation is a first order differential equation with time dependent coefficients. Thus, it has a complex behavior.

3. Thermal comfort

Fundamental goal of HVAC is to provide comfort in any condition. Comfort is vague. ASHRAE defines com-

fort as "condition of mind that expresses satisfaction with the thermal environment" [16]. Most controllers use temperature as feedback. However, as stated many factors affect thermal comfort and against public believe, temperature alone cannot show comfort precisely. Many different comfort indexes are suggested [17,18]. The best of them was introduced by Fanger [19]. This index has high precision for comfort prediction and can be used as feedback in air conditioning controller [20].

3.1. PMV

Generally, thermal comfort is achieved by variation in environmental and personal factors inside the cabin. Environmental factors are air temperature, mean radiant temperature, air velocity and relative humidity. Personal factors include activity level and clothing insulation. These six variables interact and finally a number that indicates the thermal comfort can be calculated. Fanger's PMV gives the expected degree of thermal comfort in relation to the above-mentioned six thermal parameters. Fanger's PMV is given by Eq. (13) [19]

$$\begin{aligned}\mathrm{PMV} = {} & (0.028 + 0.3033\,\mathrm{e}^{-0.036M}) \cdot \{(M - W) \\ & - 3.05[5.733 - 0.000699(M - W) - \mathrm{Pa}] \\ & - 0.42[(M - W)] - 0.0173M(5.867 - \mathrm{Pa}) \\ & - 0.0014M(34 - T_{\mathrm{a}}) - 3.96 * 10^{-8}\mathrm{fcl}[(T_{\mathrm{cl}} + 273)^4 \\ & - (T_{\mathrm{mrt}} + 273)^4] - \mathrm{fcl} \cdot h_{\mathrm{c}}(T_{\mathrm{cl}} - T_{\mathrm{a}})\}, \end{aligned} \tag{13}$$

$$\begin{aligned}T_{\mathrm{cl}} = {} & 35.7 - 0.028(M - W) \\ & - 0.155I_{\mathrm{cl}}\{3.96 * 10^{-3}\mathrm{fcl}[(T_{\mathrm{cl}} + 273)^4 - (T_{\mathrm{mrt}} + 273)^4] \\ & - \mathrm{fcl} \cdot h_{\mathrm{c}}(T_{\mathrm{cl}} - T_{\mathrm{a}})\}, \end{aligned} \tag{14}$$

$$h_{\mathrm{c}} = \begin{cases} 2.38(T_{\mathrm{cl}} - T_{\mathrm{a}})^{0.25} & 2.38(T_{\mathrm{cl}} + T_{\mathrm{a}})^{0.25} \geqslant 12.1\sqrt{V_{\mathrm{air}}}, \\ 12.1\sqrt{V_{\mathrm{air}}} & 2.38(T_{\mathrm{cl}} + T_{\mathrm{a}})^{0.25} \geqslant 12.1\sqrt{V_{\mathrm{air}}}. \end{cases} \tag{15}$$

The parameters are defined as follows:

PMV: predicted mean vote.
M: metabolism (W/m^2).
W: external work, equal to zero for most activity (W/m^2).
I_{cl}: thermal resistance of clothing (Clo).
fcl: ratio of body's surface area when fully clothed to body's surface area when nude.
T_{a}: air temperature (°C).
T_{mrt}: mean radiant temperature (°C).
V_{air}: relative air velocity (m/s).
Pa: partial water vapor pressure (kPa).
h_{c}: convection heat transfer coefficient (W/m^2 k)
T_{cl}: surface temperature of clothing (°C).

Table 1 shows the relationship between PMV, thermal sensation and physiological stress level [21].

Table 1
Relationship between PMV and thermal sensation

PMV	Thermal sensation	Physiological stress level
	Very cold	Extreme cold stress
-3.5 ----------		
	Cold	Strong cold stress
-2.5 ----------		
	Cool	Moderate cold stress
-1.5 ----------		
	Slightly cool	Slight cold stress
-0.5 ----------		
	Comfortable	No thermal stress
0.5 ----------		
	Slightly warm	Slight heat stress
1.5 ----------		
	Warm	Moderate heat stress
2.5 ----------		
	Hot	Strong heat stress
3.5 ----------		
	Very hot	Extreme heat stress

As stated before, six inputs are needed for calculation of PMV. Therefore, some researchers prefer to use other indices [22].

3.2. PMV simplification

PMV has six inputs and thus requires six sensors. We propose a simpler form of PMV where cabin air temperature and the air velocity are the only two variables and are calculated from Eqs. (11) and (12). The remaining four variables are assumed constant. This will simplify the problem without introducing significant error. To verify this assumption all four variables were simultaneously first increased and next decreased by 10% from the mean values used in this article. PMV was calculated and found to vary from −0.6 to +0.3 which is close to comfort zone (−0.5 to +0.5) defined by ASHRAE [16].

Mean values used for PMV are as follows:

- Passengers in the cabin are usually at rest while the driver has a slightly higher activity level. Therefore metabolic activity of about 1 mat and 1.5 mat are assumed for the passenger and the driver [16].
- Automobile cooler works in warm months and common cloths in these months have low thermal insulation. Table 2 shows various kinds of cloths with their thermal insulation [16]. Clothing insulation value may be expressed by clo units where 1.0 clo is equivalent to 0.155 m^2 K/W. Thermal insulation of 0.7 is an average and is assumed for this study.
- The influence of relative humidity on thermal comfort is the least among all other factors. In fact, people can feel comfortable in a wide range of relative humidity (20–70%) as long as the operative temperature is within comfort zone [19,16] (Fig. 4). Therefore, constant humidity level of 50% is assumed.
- Mean radiant temperature (MRT) is defined as the uniform temperature of an imaginary enclosure in which

Table 2
Common cloths in warm cloths

Ensemble description	I_{cl} (clo)
Walking shorts, short-sleeved shirt	0.36
Trousers, short-sleeved shirt	0.57
Trousers, long-sleeved shirt	0.61
Same as above, plus suit jacket	0.96
Sweat pants, sweat shirt	0.74
Knee-length skirt, short-sleeved shirt, panty hose, sandals	0.54
Knee-length skirt, long-sleeved shirt, full slip, panty hose	0.67
Ankle-length skirt, long-sleeved shirt, suit jacket, panty hose	1.1
Long-sleeved coveralls, T-shirt	0.72
Overalls, long-sleeved shirt, T-shirt	0.89

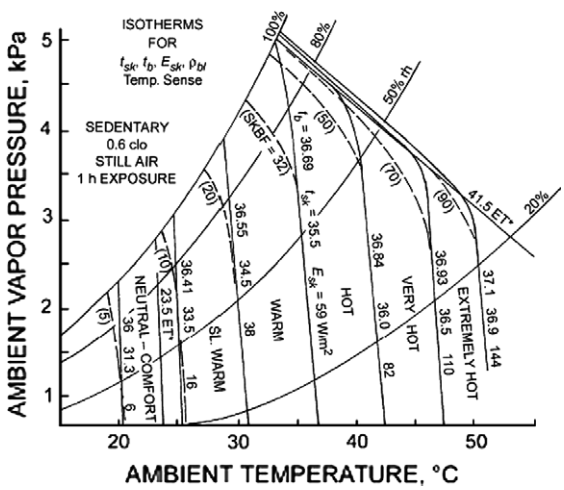

Fig. 4. Effect of relative humidity on comfort [16].

radiant heat transfer from the human body equals the radiant heat transfer in the actual nonuniform enclosure [16]. Two methods are suggested for measuring MRT. The first method utilizes a black globe, two thermometers and air velocity meter. The second method uses absolute surface temperature of the surrounding surfaces and angle factors between the person and the surrounding surfaces [23]. Both methods require multiple sensors and are difficult to measure. For simplification, some researchers assume MRT is equals to inside air temperature [24–26]. This assumption is also used in this study.

4. Fuzzy controller

Fuzzy logic was born in 1965 by Zadeh [27]. Nowadays, it is widely used in industrial applications. Fuzzy logic can model the nonlinear relationship between inputs and outputs. It can simulate the operator's behaviour without use of mathematical model [28]. It is a method that transfers human knowledge into mathematics. Incomplete, vague and/or inaccurate expert knowledge is formulated with the aid of if–then rules. Each rule explains a nonlinear relationship between inputs and outputs. All rules together define a linguistic model. For more information about fuzzy logic see Zimmerman [29].

Fuzzy control is the most practical branch of fuzzy logic. Fuzzy control is inherently vague and nonlinear, thus it is suitable for systems with this behavior. Automobile air conditioning system is also nonlinear and complex therefore, it is difficult for conventional methods to control it well [6]. This makes fuzzy control a good choice for controlling this system.

4.1. Fuzzy controller with temperature feedback

In most air conditioning controllers, temperature is used as feedback and a fix temperature is the controller goal. Block diagram of this controller for automobile cabin is given in Fig. 5.

Inputs to fuzzy controller are the error and the changes of error. Outputs are blower power and the position of temperature door for regulating the necessary blend of hot and cold air. Error is defined by the following equation:

$$\text{error} = T_{\text{d}} - T_{\text{cabin}}. \tag{16}$$

Desired temperature is adjusted by the automobile driver which in warm months is about 22 °C. Formation of suitable fuzzy sets is important in designing of fuzzy controller. Triangular fuzzy sets are chosen for this controller and are equally divided (Fig. 6).

The min–max limits are adjusted based on the dynamics of the system and the control goal. For this system, the min–max limits are manually selected as indicated in Table 3.

Maximum number of rules is equal to multiplication of the number of input membership functions. It is clear that a large number of rules are more difficult to define. Therefore, to simplify the problem three membership functions are selected for each input and output variables. This results into nine rules for each output. The state evaluation fuzzy control rule [34] is applied for controlling this system. The fuzzy inference logic uses the Min–Max [29] to operate the fuzzy control rules. Finally, the center of area method [29] is employed to defuzzify the output variables. This defuzzzification method is simple, accurate and more suitable for the system's dynamics.

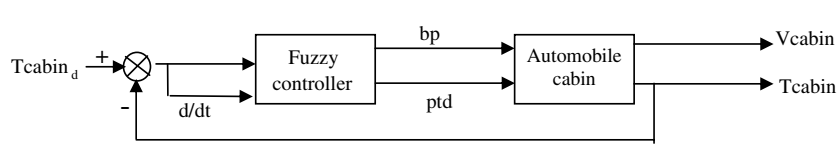

Fig. 5. Temperature control with temperature feedback.

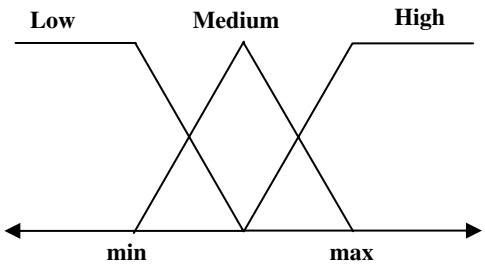

Fig. 6. Fuzzy sets.

Table 3
Suggested interval for variables

	Min	Max
Temperature error	−6	6
Temperature error_dot	−1	1
Blower power	−0.15	1.45
Position of temperature door	0	1.8

Simulation is performed assuming 35 °C outside temperature environment and zero fresh air entering the system. It is assumed that the hot soak is finished and the initial temperature in cabin is equal to the outside temperature. Controller regulates the outputs in a manner to achieve the desired temperature in the cabin. Results of the fuzzy controller with temperature feedback are shown in Fig. 7.

Thermal comfort is calculated by the simplified PMV index during simulation. Controller achieves the desired temperature, however, it cannot achieve the zero PMV as shown in Fig. 8.

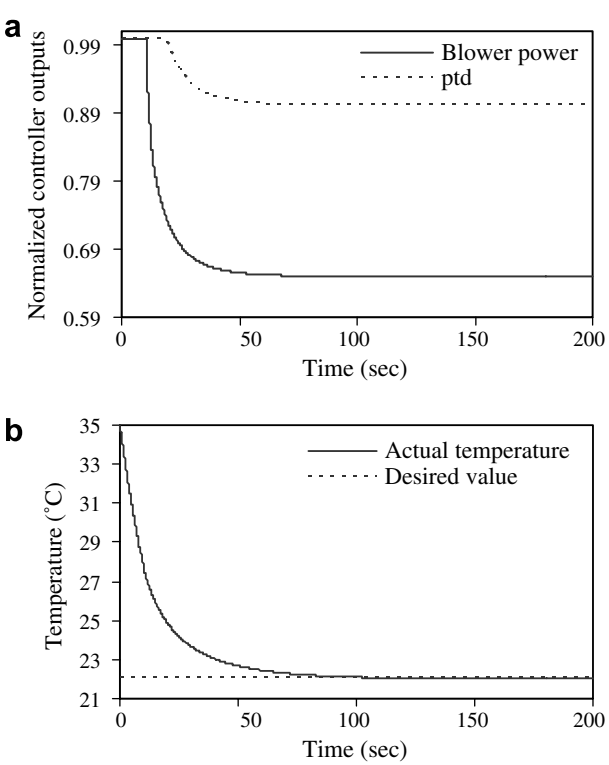

Fig. 7. (a) Normalized controller outputs and (b) temperature variation in cabin.

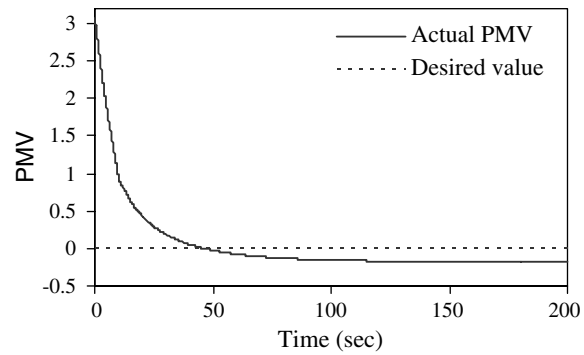

Fig. 8. PMV variation in cabin.

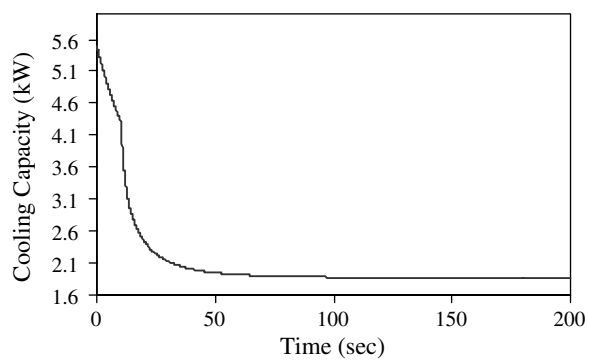

Fig. 9. Evaporator cooling capacity.

Minimal energy consumption is another performance criterion used in this study. It means that the compressor power should be as low as possible. COP relates the evaporator cooling capacity to the compressor power. Therefore, evaporator cooling capacity may be used as a good index for compressor power

$$\mathrm{COP} = \frac{\dot{Q}_e}{\dot{W}_c} \Rightarrow \dot{W}_c = \frac{\dot{Q}_e}{\mathrm{COP}}. \tag{17}$$

Jabardo et al. [30] performed research on automotive refrigeration cycle. They showed if the evaporator cooling capacity is increased then COP would decrease. Therefore, regards to Eq. (17), increment in cooling capacity has a two-fold effect on increasing compressor power. Fig. 9 shows the evaporator cooling capacity for the system during the simulation.

4.2. Fuzzy controller with thermal comfort feedback

As stated before, temperature does not best describe the thermal comfort and therefore controller with temperature feedback cannot achieve desired comfort. A better solution is to use controller with PMV feedback as shown in Fig. 10.

Desired PMV is zero which indicates the comfort condition. Suggested intervals for variables are indicated in Table 4.

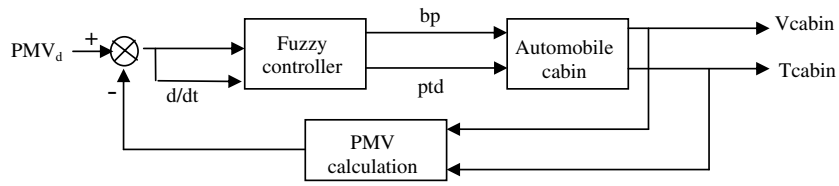

Fig. 10. Controller with PMV feedback.

Table 4
Suggested interval for variables

	Min	Max
PMV error	−3.5	3.5
PMV error_dot	−1.5	1.5
Blower power	−0.1	1.33
Position of temperature door	0	1.8

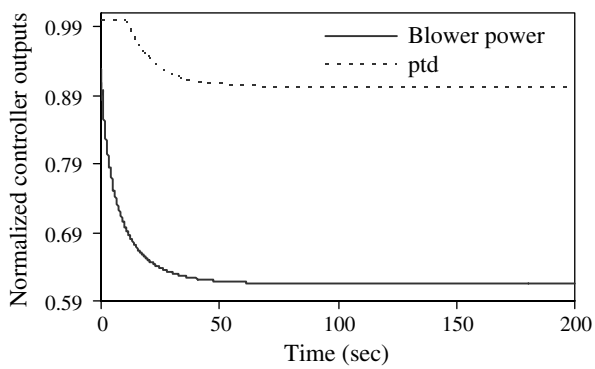

Fig. 11. Normalized controller outputs.

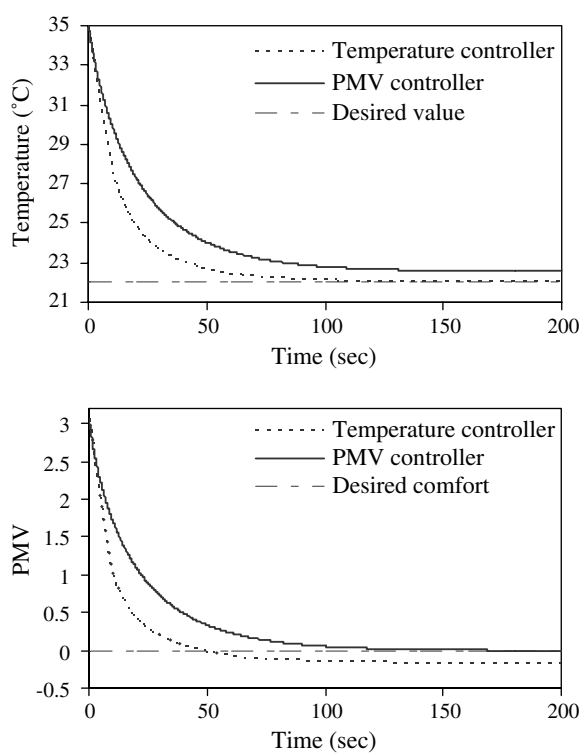

Fig. 12. PMV and temperature variations.

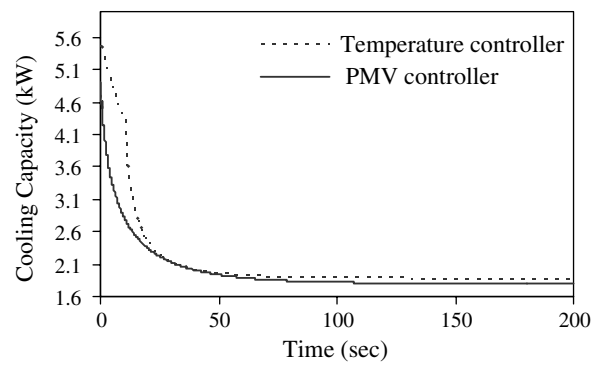

Fig. 13. Evaporator cooling capacity.

The two simulation conditions of 35 °C outside temperature and zero fresh air entering the system are the same as the previous controller (temperature controller). Controller outputs are plotted in Fig. 11. Temperature and PMV comparison between the two controllers are shown in Fig. 12.

Comparison shows that the PMV controller better controls comfort than temperature controller. Additionally, evaporator cooling capacity is calculated and compared for the two controllers (Fig. 13).

It is clear that the controller with PMV feedback has lower energy consumption. This controller achieves comfort while minimizing energy usage therefore, reaching more of air conditioning system goals.

5. Tuning fuzzy controller with genetic algorithm

Fuzzy systems design can be divided into three main stages; namely, the selection of a proper set of input and output variables and their related universes of discourse, the identification of a suitable structure for the fuzzy system and the extraction of an optimal fuzzy rule-base. The most crucial task in fuzzy systems design is the formation of proper membership function with fuzzy rules. This directly affects the overall performance of the system. If the designer has primary knowledge of system performance, he can use that as a good starting point for the design of the fuzzy control system. However, if no primary knowledge is available, formation and tuning of membership functions would not be an easy task. Identification of fuzzy system parameters is also possible by having input–output data. However, data creation is not an easy task and the data may be noisy and inaccurate. Furthermore, fuzzy systems do not have ability to learn [31] and

complementary methods such as artificial neural network and evolutionary algorithms should be used for this purpose.

Recently, evolutionary algorithms and especially genetic algorithm are proposed as an instrument to optimize fuzzy systems. Genetic algorithm (GA) is general and a global optimization method which is based on the natural evolution theory. GA is suitable for not well defined as well as irregular search spaces. Optimization problem is defined as the objective function. Variables are coded as chromosomes and each chromosome is an answer to the problem. Fitness is assigned to each chromosome with respect to the objective function. Fittest chromosomes generate the next population through reproduction, crossover and mutation. Interested readers refer to [32].

5.1. General procedure for tuning fuzzy controller using genetic algorithm

Important parameters such as membership functions and fuzzy rules are first coded to chromosomes. Fitness value is given to each chromosome based on performance of fuzzy controller. Next, GA operators generate the next generation of population. This process continues until the desired performance is achieved or the number of generation exceeds a specific number (Fig. 14).

5.2. Tuning the existing membership functions

If the rule-base is small, the if–then structure of fuzzy rule is easy to understand and build with priori knowledge. The state evaluation fuzzy control rule and/or state trajectory approach can be used for defining fuzzy rules [33]. The control goals can be easily obtained by adjusting the membership functions. The formation of acceptable fuzzy membership functions is a subjective and time consuming task, thus GA is use to search and optimize the membership functions. In this study, the min–max limits of the membership functions are defined and GA finds the best limit for each input–output variable. Min–Max limits are normalized to (0, 1) and then coded to chromosomes. Controller has two inputs (PMV, PMV-dot) and two outputs (blower power, ptd), thus the length of each chromosome is equal to eight Genes (Fig. 15).

Achieving comfort is the desired response of fuzzy controller. Initially GA is applied to optimize PMV without considering energy consumption. Zero value for PMV indicates optimum thermal comfort. Absolute summation of the differences between calculated and zero PMV during simulation is selected as the objective function for GA. Therefore GA attempts to minimize this difference by adjusting the membership functions

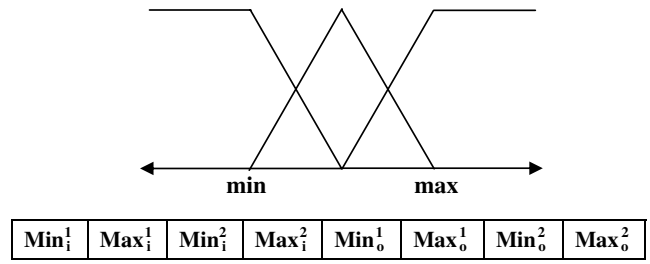

Fig. 15. Chromosome coding.

$$\text{Fitness function } 1 = \sum |\text{PMV} - 0|. \tag{18}$$

Results as indicated in Figs. 16 and 17 show thermal comfort is achieved faster with the GA-tuned parameters, however, energy consumption is increased due to an increase in cooling capacity. Clearly, this increase in energy consumption is not acceptable.

Minimizing energy consumption while achieving optimum PMV is next considered. As indicated before, a good index for compressor power and energy consumption is evaporator cooling capacity. The summation of evaporator cooling capacity during each simulation is the index used

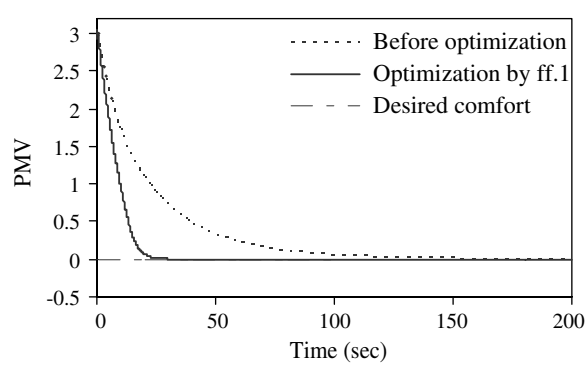

Fig. 16. PMV in cabin.

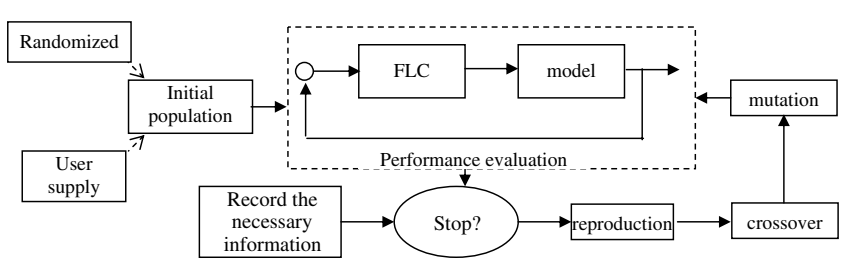

Fig. 14. General GA optimization process.

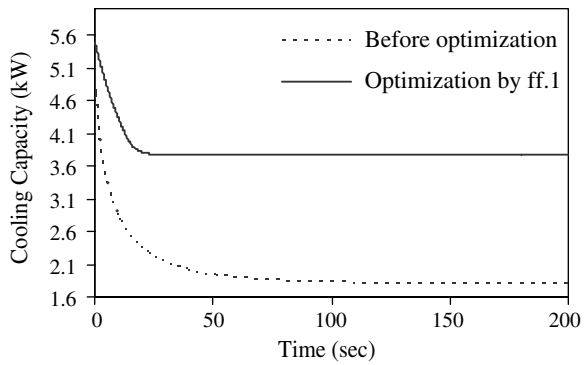

Fig. 17. Evaporator cooling capacity.

for energy consumption. These two goals result in a two-objective optimization problem, i.e., minimizing both the comfort error and energy consumption. The multi-objective goal can be converted into a single objective problem. One way to combine these goals is by applying proper weights to each goal

$$\text{Fitness function } 2 = w_1 \cdot \sum |\text{PMV} - 0| + w_2 \cdot \sum Q_r. \tag{19}$$

The weights w_1 and w_2 are manually selected to produce approximately equal effects for both cooling capacity as well as PMV error. The optimized limits which minimize the objective function (Eq. (19)) are listed in Table 5.

Results of fuzzy controllers before and after optimization with fitness function-1 (ff-1) and fitness function-2 (ff-2) are shown in Fig. 18.

As shown in Fig. 18 the optimized fuzzy with ff-2 reaches thermal comfort approximately 15 s later than the controller with ff-1. However, this slight delay in reaching comfort is well compensated by the significant reduction in fuel consumption. It can be concluded that optimization using ff-2 reaches thermal comfort while reducing energy consumption.

5.3. Robustness analysis

Automobile cabin is affected by many random and uncontrollable parameters. Variation in uncontrolled parameters is one of the most important sources affecting system performance. These are part of the system model but are not under designer control and may strongly influence the behavior of the system. A good controller must be robust to changes in these variables.

Table 5
Tuned limits of variables

	Min	Max
PMV error	−0.7353	2.6017
PMV error_dot	−4.8533	0.2354
Blower power	−0.7013	1.7729
Position of temperature door	0.3116	1.6376

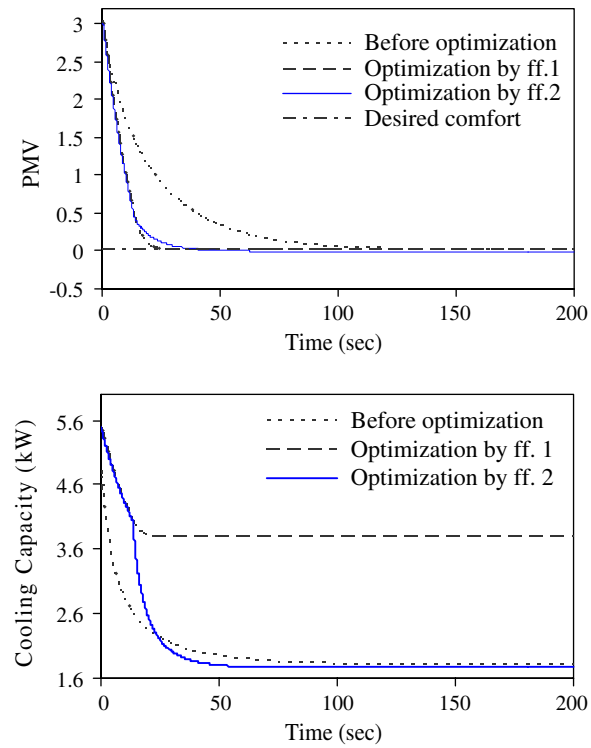

Fig. 18. Fuzzy controller before and after optimization.

Optimization and robustness often work against each other. Therefore, robustness analysis should be performed after optimization to insure the effectiveness of controller over a wide range of conditions. Robustness is a characteristic of controller which minimizes the effect of uncertainty or variation in system parameters without eliminating the source of the uncertainty or variation.

In this study, thermal load is the most important uncontrollable parameter that affects system behavior. Thermal load is affected by variations such as outside air temperature, sun radiation, opening the automotive windows and doors, ratio of fresh air to re-circulated air. Controller

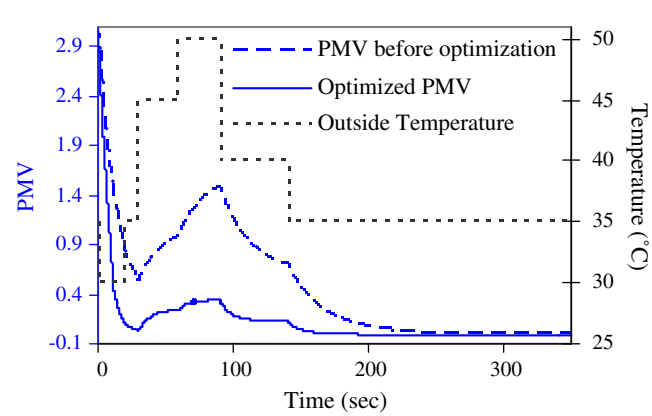

Fig. 19. PMV during temperature variation.

must be robust to changes in these parameters. To show the controller robustness we assume that the outside air temperature, an uncontrolled parameter, varies during the simulation while other conditions and parameters remain unchanged. As can be seen from Fig. 19, the controller response during temperature changes is quite reasonable and quickly brings PMV to zero value. Therefore, the optimized controller is robust to parameter variations. The response of the controller before optimization is also shown. It is clear that this controller is also robust to temperature variation.

6. Conclusions

Poor interior condition of automobile contributes to traffic accidents as well as discomfort in long distance drives. Thermal comfort is one of the most important comfort factors. Automobile cabin thermal environment is complex, continually varies during time and cannot be described with temperature alone. Important parameters that affect thermal comfort are cabin air temperature, relative humidity, air velocity, environment radiation, activity level of passengers and clothing insulation. PMV index which combines the above parameters is used to indicate thermal comfort in cabin.

In this paper thermal comfort for Peugeot 206 automobile is studied. A simplified form of PMV is introduced where cabin air temperature and the air velocity are the only two variables. This simplification is made without introducing significant error. The simplified PMV index is used as the feedback in fuzzy controller instead of temperature. Results indicate PMV controller better controls comfort than temperature controller. Genetic algorithm is next used to improve the performance of the fuzzy controller. Results indicate desired PMV is reached faster with the GA optimized controller.

Providing thermal comfort while minimizing energy consumption was the next goal of the controller. Evaporator cooling capacity was selected as criterion for energy consumption. These two goals result in a two-objective optimization problem, i.e., minimizing both the comfort error and energy consumption. The multi-objective goal is converted into a single objective problem. Genetic algorithm is next used to improve the performance of fuzzy controller. It is shown that after optimization controller reaches thermal comfort quicker while minimizing energy consumption. Finally, robustness analysis is performed to show the robustness of both optimized and not optimized controllers to variations in system variables. Outside air temperature was varied and controller response was measured. Results indicate both controllers perform well to temperature variations and therefore are considered robust.

Acknowledgements

We gratefully acknowledge the guides of Dr. Y. Ahmadi, Dr. M. Farshad and Mr. N. Sherafati. We also would like to acknowledge Mr. Sajedi for his contribution in performing the experiments.

References

[1] H.A.M. Daanen, E. Vliert, X. Huang, Driving performance in cold, warm, and thermoneutral environments, Appl. Ergon. 34 (2003) 597–602.
[2] T. Zlatoper, Determinants of motor vehicle deaths in the United States: a cross-sectional analysis, special issue: theoretical models for traffic safety, Accid. Anal. Prev. 23 (5) (1991) 431–436.
[3] Editorial Team, The Global Market for Automotive Heating, Ventilation, Refrigeration and Air Conditioning, Just. Auto, 2001.
[4] M.A. Lambert, B.J. Jones, Automotive adsorption air conditioner powered by exhaust heat. Part 1: conceptual and embodiment design, Proc. IMechE Part D: J. Automobile Eng. 220 (2006) 959–972.
[5] T. Tabe, K. Matsui, T. Kakehi, M. Ohba, Automotive climate control, IEEE Control Syst. Mag. (1986) 20–24.
[6] L.I. Davis, T.F. Sieja, R.W. Matteson, G.A. Dage, R. Ames, Fuzzy logic for vehicle climate control, in: 3rd IEEE Int. Conf. Fuzzy Systems, 1994, pp. 530–534.
[7] K.C. Wei, G.A. Dage, An Intelligent Automotive Climate Control System, 1995, pp. 2977–2982.
[8] H. Zhong et al., Controlling indoor air temperature in a automobile with fuzzy controller via air-conditioning system, Shanghai Jiaotong Daxue Xuebao 35 (8) (2001) 1163–1166.
[9] H.M. DuroviC, B.D. KovaZeviC, Control of heating, ventilation and air conditioning system based on neural network, in: 7th IEEE Seminar on Neural Network Application in Electrical Engineering, 2004.
[10] S. Shimisou, H. Hara, F. Asakawa, Analyzing on air conditioning of a passenger vehicle, Int. J. Vehicle Des. 4 (3) (1993).
[11] J. Selow, Toward a Virtual Vehicle for Thermal Analysis, SAE Technical Paper 971841.
[12] A.M. Kalteh, A.H. Kakai, B. Farhani, Investigate the performance of Peugeot 206 cooler in different climate condition, in: 8th Int. and 12th Annual Mechanical Engineering Conference, 2004 (in Persian).
[13] V. Klimenko, A generalized correlation for two-phase forced flow heat transfer, Int. J. Heat Mass Transfer 31 (3) (1988) 541–552.
[14] W.M. Kays, A.L. London, Compact Heat Exchangers, third ed., McGraw Hill, New York, 1984.
[15] F.P. Incropera, D.P. De Witt, Introduction to heat transfer, fourth ed., McGraw Hill, 2002.
[16] ASHRAE Handbook – Fundamentals, Chapter 8, Thermal Comfort, 2001.
[17] A.P. Gagge, A.P. Fobelets, L.G. Berglund, A standard predictive index of human response to the thermal environment, ASHRAE Trans. 92 (1986) 709–731.
[18] M. Sherman, A simplified model of thermal comfort, Energy Buildings 8 (1985) 37–50.
[19] P.O. Fanger, Thermal Comfort, Analysis and Applications in Environmental Engineering, McGraw Hill, 1972.
[20] M. Hamdi, G. Lachiver, F. Michaud, A new predictive thermal sensation index of human response, Energy Buildings 29 (1999) 167–178.
[21] Matzarakis, H. Mayer, Heat stress in Greece, Int. J. Biometeorol. 41 (1997) 34–39.
[22] Saunders, Automotive climate control based on thermal state estimation, PhD thesis, University of Glasgow, England, 2002.
[23] ISO 7726. Thermal Environments – Instruments for Measuring Physical Quantities, International Standard Organization, Geneva, 1998.
[24] M.S. Jang, C.D. Koh, I.S. Moon, Review of thermal comfort design based on PMV/PPD in cabins of Korean maritime patrol vessels, Building Environ. 42 (2007) 55–61.

[25] J. Toftum, A.S. Jorgensen, P.O. Fanger, Upper limits for indoor air humidity to avoid uncomfortably humid skin, Energy Buildings 28 (1998) 1–13.
[26] I. Atmaca, A. Yigit, Predicting the effect of relative humidity on skin temperature and skin wettedness, J. Thermal Biol. 31 (2006) 442–452.
[27] L.A. Zadeh, Fuzzy sets, Inform. Control 8 (1965) 338–353.
[28] U. Bersini, P.C. Cacciabue, Simulating operator behavior in process control by a goal oriented approach and fuzzy logic formalism, Pergamon Press, New York, 1987.
[29] H.J. Zimmerman, Fuzzy Set Theory And Its Applications, Springer, 2001.
[30] J. Jabardo, W.G. Mamani, M.R. Ianella, Modeling and experimental evaluation of an automotive air conditioning system with variable capacity compressor, Int. J. Refrig. 25 (2003) 1157–1173.
[31] K.H. Lee, First Course on Fuzzy Theory and Application, Springer, 2005.
[32] R.L. Haupt, S.E. Haupt, Practical Genetic Algorithms, second ed., Wiley, New Jersey, 2004.
[33] K. Tanaka, An Introduction to Fuzzy Logic for Practical Applications, Springer, 1997.
[34] CC. Lee, Fuzzy logic in control systems: fuzzy logic—part I and II, IEEE Trans. Syst. Man Cybern. 20 (1990) 404–435.