A Dissertation

on

Deep Neural Network Based Estimation for Thermal Comfort Index

Submitted in partial fulfillment of the requirements for the award of the degree

of

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in

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Submitted by

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CANDIDATE'S DECLARATION

I hereby declare that the work presented in this dissertation "***Deep Neural Network Based Estimation for Thermal Comfort Index***" towards the fulfillment of the requirements for award of the degree of ***Master of Technology in Computer Science and Engineering***, submitted to the Department of Computer Science and Engineering, ***Indian Institute of Technology-Roorkee, India*** is an authentic record of my own work carried out during May 2017 to May 2018 under the guidance of ***Dr. Sudip Roy***, Assistant Professor, Department of Computer Science and Engineering, Indian Institute of Technology, Roorkee.

The content presented in this dissertation has not been submitted by me for the award of any other degree of this or any other institute.

Date:

Place: Roorkee

(Anirban Mitra)

CERTIFICATE

This is to certify that the statement made by the candidate in the declaration is correct to the best of my knowledge and belief.

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ABSTRACT

Thermal Comfort indicates human interpretation of comfort level of an environment. Predicting Thermal Comfort for a certain future date can have several applications. Predictive Mean Vote (PMV) is one of the most used measure to express thermal comfort index, both indoor and outdoor. Many of the parameters involved are needed to be synthesized which adds to the complexity of it. Many techniques and algorithms to estimate it using only some of the parameters involved have been proposed till date aiming to improve the accuracy. Fuzzy Neural Network (FNN)s have been particularly successful in this scenario generating suitable sets of rules. Improving the accuracy a step further while choosing optimized number of parameters contribute to smoother and expanded applications. Convolutional Neural Network (CNN) is an essential Deep Neural Network (DNN) technique. It is primarily used shrink or convolve large data into smaller versions by keeping essential details intact. These smaller versions are used to classify (or in some case estimate using regression) using softmax layers or ReLU layers. In this work, focus was on combining modified FNN with suitable layers of CNN and/or traditional neural network to estimate PMV by regression with greater accuracy.

DEDICATION

To mom, dad and you

ACKNOWLEDGEMENTS

I would never have been able to complete my dissertation without the guidance of my supervisor, and support from my family and loved ones. I would like to express a thankful note to my supervisor, **Dr. Sudip Roy**, for his guidance. I am also grateful to the Department of Computer Science and Engineering of Indian Institute of Technology Roorkee for providing valuable resources to aid my research.

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Chapter 1

INTRODUCTION

Thermal comfort of any region, indoor and outdoor is a matter of interest for travelers, residents, business-people, workers etc. If possible, a prediction of certain area or indoor system, could have several applications such as: travel suitability prediction, thermal stress prediction for resident and workers to help them decide their working hours. Even in indoor one could tune ventillations or Air-conditioning according to predictions.

The prime difference between naturally ventilated (NV) and HVAC buildings is that NV systems are unable to be tuned as per occupant feeling (indoor heat exchange are shown in Fig. 1.1).

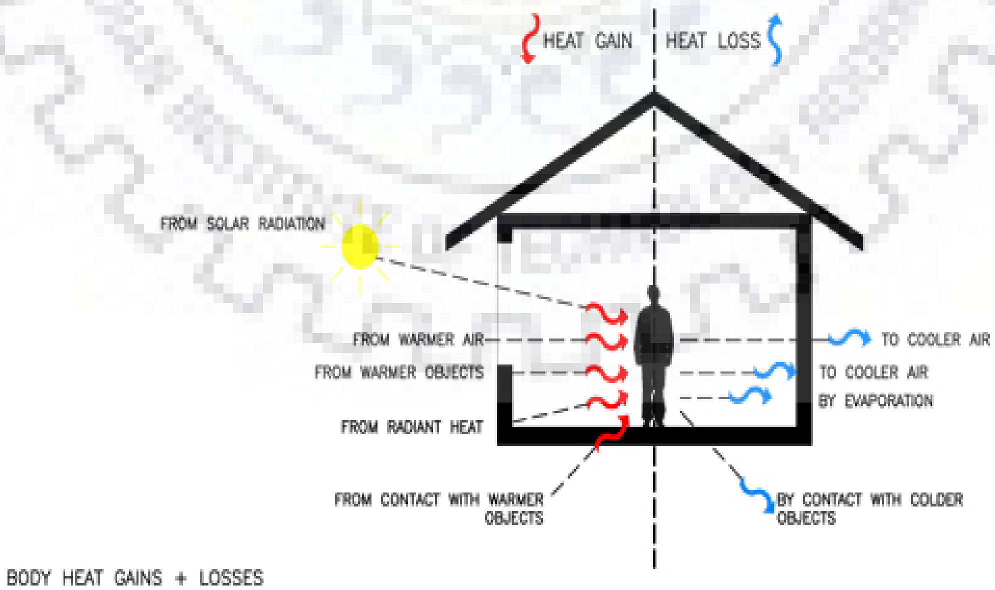

Figure 1.1: Indoor Heat Exchange in Human Body [1]

Being a semi-closed system, NV buildings' environment tends to get affected by change in air-velocity, air temperature, relative humidity, etc. Comfort level in the context of human body is often associated with thermal comfort felt by individuals. Thermal comfort is referred to as the condition of mind that expresses satisfaction with the thermal environment (depicted in Fig. 1.2). However, this thermal comfort level is also greatly associated

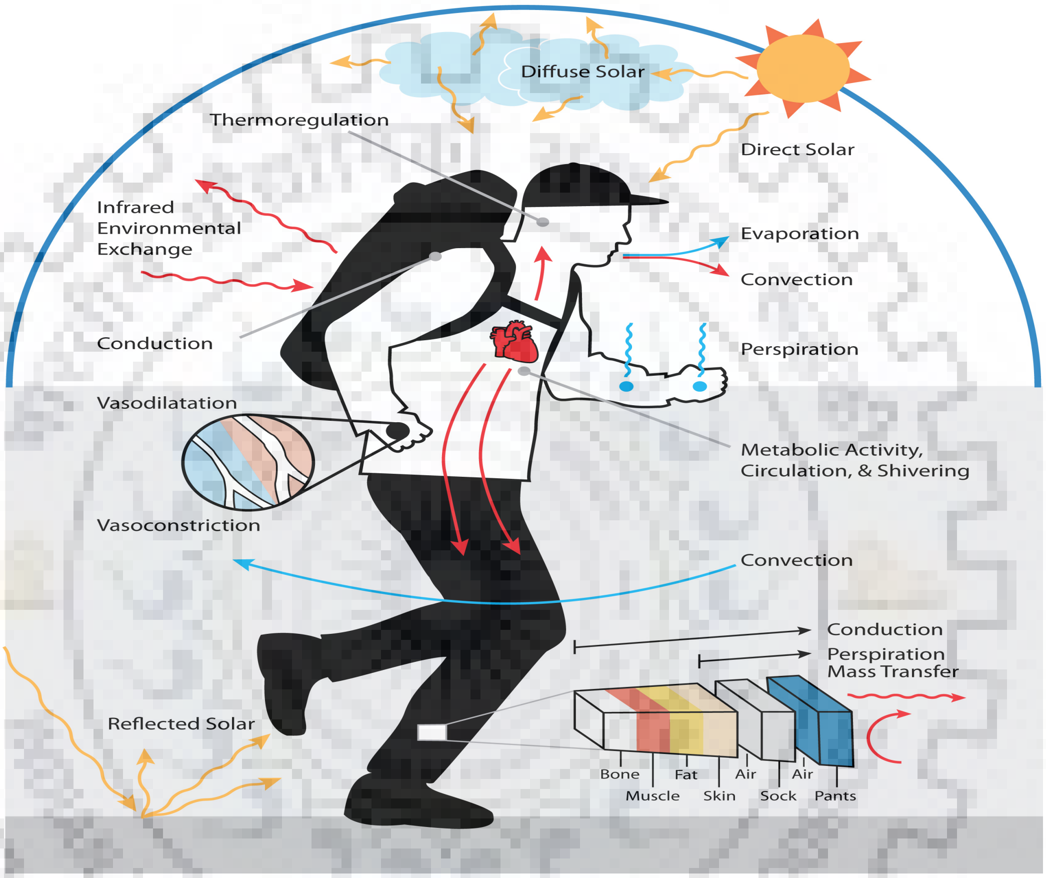

Figure 1.2: General Heat exchange in Human Body [2]

with relative humidity, air-velocity, mean radiant temperature, metabolic rate, clothing factor along with air temperature [5]. As a choice of comfort index, PMV is a widely used one and uses all the six parameters mentioned previously along with some synthesized variables. It is often very difficult to estimate PMV in real time because of the complexity, but from meteorological data, it is easy to retrieve only some of the parameters mentioned.

Approaches have been developed to estimate the PMV value from few of the parameters. This work aims at solving the estimation problem with a novel architecture comprised of fuzzy system and Deep Neural Network (DNN) along with analysis of the system. Our choice of DNN is Convolutional Neural Network (CNN) used primarily for regression on the output of fuzzy neural network to estimate PMV. Although CNNs are proved to shrink large data chunk into small one and then classify, this work observes its' ability in regression using its' convolving and pooling property.

1.1 Motivation and Objective

CNN is primarily used for classification using deep layer techniques, converting large data to smaller, significant data-chunks. On the other hand, in order to extend the use of PMV prediction as comfort index both indoor and outdoor, interest lied in finding a different technique of estimating PMV and/or possibly with better results. *Li et al.* [6] and *Yifan et al.* [7] was able to achieve significant accuracy (RMSE 0.2 and RMSE 0.045, respectively) using fuzzy sets and neural networks. One of the purposes of this work was to establish the fact that deep architectures like CNN could as well be used to perform regression-like tasks and possibly find better results in estimating PMV.

In this work, attempt was made to use CNN for regression along with fuzzy sets for PMV estimation. This work, if successful would be able to produce nearly accurate PMV values for any date given meteorological parameters such as Air Temperature, Relative Humidity, Air Velocity, Metabolic rate, Clothing Factor and Mean Radiant Temperature obtained from remote sources. For this purpose a more open-source data has been considered. Along with the final outcome, focus was put on choice of parameters and behavior of various aspects of neural network architecture with the result.

1.2 Contribution of the Dissertation

This dissertation presents a novel architecture which uses CNN in regression problem in order to estimate PMV. Traditional ANFIS model is modified using fuzzy-set values and expanded in a particular way to be used here. A particular combination and sequence of convolve and pooling layers were appended to ANFIS model to perform this regression of PMV. As we are restricted to the choice of input parameters for applying this in real-world scenario, this work demonstrates suitable optimized choice of parameters for best result and their inter-dependency. As we were interested in extending scope of this work to both indoor and outdoor, both NV and HVAC building data were considered from a open-source platform. This approach also improves the error of estimating PMV compared to works done previously.

1.3 Organization of Dissertation

This dissertation has been divided in chapters.

- Chapter 1 provides introduction of Predicted Mean Vote (PMV) along with its' extended scope of applications in various fields and why prediction of it is an important aspect. It also discusses about CNN, Fuzzy-Neural Networks and how these can be used to do the same.
- Chapter 2 describes analysis of various thermal comfort indexes and their relative applicability comparison. Further it gives necessary background on Adaptive Fuzzy Neuro Fuzzy-Systems (ANFIS) and basics of CNN.
- Chapter 3 presents some of the most effective PMV estimation algorithms till date using combinations of fuzzy-sets and neural networks. This section also discusses about some works attempting regression using CNN.
- Chapter 4 presented the proposed Fuzzy-CNN architecture along with few variations in both implementation and input system.
- Chapter 5 provides the simulation results of work presented in this dissertation along with
- Chapter 6 provide concludes the dissertation and presents the future scope in this scenario.

Chapter 2

BASIC PRELIMINARIES

As this work will be using Adaptive-Network- Based Fuzzy Inference System (ANFIS) model along with CNN layer in the end to estimate PMV, some basics about them are presented.

2.1 Predicted Mean Vote (PMV)

PMV was developed by Fanger [8] to scale human sensation of thermal comfort, which is backed by ASHRAE. PMV was defined as a function of six parameters: Air-temperature (T_a), Relative Humidity (RH), Mean radiant air-temperature (T_R), Air-velocity (V_{air}), metabolic rate (Met), clothing factor (Clo). This quantification of thermal comfort of a group of persons is defined in a scale of -3 to +3, described in Table 1.
The PMV equation is defined as:

$$
\begin{aligned}
(0.303e^{-0.036Met} + 0.028)[(Met - W) - 3.05 \\
\times 10^{-5} \times [5733 - 6.99(Met - W) - P_a] \\
- 0.42[(Met - W) - 58.15] - 1.7 \times 10^{-5} Met(5867 - P_a) - 0.0014 \times Met(34 - T_a) \\
- 3.96 \times 10 - 8 f_c \times [(T_{cl} + 273)^4 - (T_R + 273)^4] - f_{cl} h_c (T_{cl} - T_a)]
\end{aligned}
\tag{2.1}
$$

where Met is human metabolic rate and W is external work done in W/m^2, P_a is water vapor pressure in Pa, T_a and T_R are in $^\circ C$. T_{cl} is the surface temperature of clothing, h_c is convective heat transfer coefficient (both in $^\circ C$), the ratio of clothed body surface area to naked body surface area is f_{cl}.

Table 2.1: PMV Labels

PMV Index	-3	-2	-1	0	1	2	3
Label	cold	cool	less cool	neutral	less warm	warm	hot

Some of these parameters are defined by some complex equations as:

$$T_{cl} = 35.7 - 0.028(Met - W) - Icl[3.96 \times 10^{-8} f_{cl} \times [(T_{cl} + 273)^4 - (T_R + 273)^4] + f_{cl} h_c (T_{cl} - T_a)] \quad (2.2)$$

$$h_c = \begin{cases} 12.1\sqrt{V_{air}} & \text{if } 2.38(T_{cl} - T_a)^{1/4} < 12.1\sqrt{V_{air}}. \\ 2.38(T_{cl} - T_a)^{1/4}, & \text{if } 2.38(T_{cl} - T_a)^{1/4} > 12.1\sqrt{V_{air}}. \end{cases} \quad (2.3)$$

$$f_{cl} = \begin{cases} 1.00 + 0.2 I_{cl} & \text{if } I_{cl} \leq 0.5\ Clo\ . \\ 1.05 + 0.1 I_{cl}, & \text{otherwise .} \end{cases} \quad (2.4)$$

where I_{cl} is thermal resistance of clothing (Clo) in W/m^2, P_a is calculated as:

$$P_a = \frac{P_s RH}{100} \quad (2.5)$$

P_s is saturated vapor pressure at specific temperature (°C). As seen, PMV is expected to have non-linear behavior and unrealistic to solve in real-time, which is the reason behind establishing such models to estimate its' value using choice of parameters.

As discussed, in order to estimate PMV, our work deals with fuzzy-neuro systems with certain deep layer addition. Following sub-sections are dedicated for some useful basics.

2.2 ANFIS Model

Adaptive-Network-Based Fuzzy Inference System (ANFIS) was developed by *Jang et al.* [9] using Takagi-Sugeno fuzzy model [10] to leverage fuzzy-rule strength and estimate outputs. For a rule i:

$$w_i = \mu_1^i(x_1) \times \mu_2^i(x_2) ... \times \mu_p^i(x_p) \quad (2.6)$$

where w_i is rule strength, μ_j^i is membership function for input x_j and rule i. After that the rule strengths are normalized ($\bar{w}_i$) and put into linear combination with input values in order to get output, where a_j is called consequent parameter:

$$y = \sum_i \bar{w}_i(a_0 + a_1x_1 + a_2x_2 + \ldots + a_nx_n) \tag{2.7}$$

2.3 Convolutional Neural Network (CNN)

CNNs are similar to normal feed-forward Artificial Neural Networks (ANN) except that they are specifically used to shrink or "convolve" the input into a more less dimensional or sized data-form to work upon. They generally work well on images (classification, compression, etc.). The hidden layers of CNN typically consist of 3 type of layers: convolutional layer, pooling layer and fully connected layer.

- *Convolutional Layer:* This basically converts a sub-section of input into a smaller size (mostly by performing dot product). A window of randomly initialized values is applied to convolve part of input data having identical dimension; while the window is slid by some pre-defined value. This is presented in Fig. 2.1.

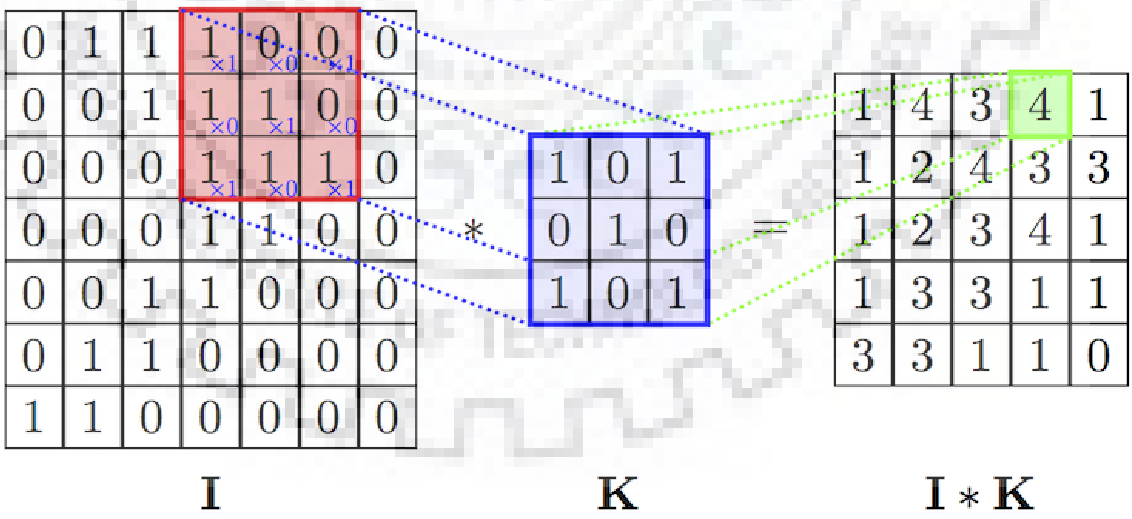

Figure 2.1: Convolutional Layer Funcitioning [3]

- *Pooling Layer:* Pooling layer performs downsampling i.e. transforms region of input into singular value. This is generally done by taking maximum (max-pool, presented in Fig. 2.2), minimum (min-pool) or average (average-pool).

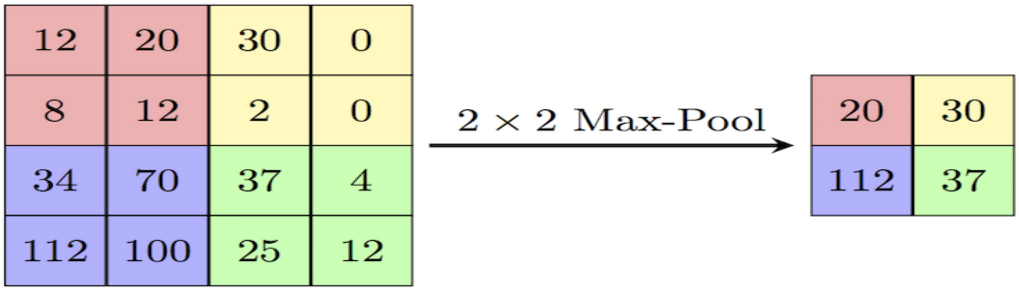

Figure 2.2: Pooling (Max) Layer Funcitioning [4]

- *Fully Connected Layer:* Here every neuron in previous layer is connected to every neuron in next layer. This layer is generally applied after convolving and/or pooling in order to get classification or regression value.

The relative positioning and deciding number of layers is specific to problem scenarios.

Chapter 3

LITERATURE SURVEY

The purpose of developing a model to estimate Thermal Comfort for future days using few of the available parameters from meteorological data, was that it can be used in applications like: travel safety check for a certain region, generating time-series comfort index trend for a region for study purpose, choosing an area for living etc. This thermal comfort index was not limited to PMV, in fact there were various other ways developed for estimating Thermal Comfort before and after PMV was developed. Some of them are presented below.

3.1 Various Thermal Comfort Indexes

Before PMV was developed by Fanger et al. [8], other comfort indexes like PET, SPMV, SET were proposed. Even after PMV was proposed PPD and UTCI came into picture.

3.1.1 Physiological Equivalent Temperature (PET)

Höppe et al. [11] defined PET as the physiological equivalent temperature at given place (indoors or outdoors) and is equivalent to the air temperature at which, in a indoor setting, the heat balance of the human body (work metabolism 80 W of light activity, added to basic metabolism; heat resistance of clothing 0.9 clo) is maintained with core and skin temperatures equal to those under the conditions being assessed. The assumptions that were made for indoor climate references are: Mean Radiant Temperature equals Air Temperature, Air Velocity is set to 0.1 m/s, water Vapour Pressure is set to 12 hPa (approximately equivalent to a relative humidity of 50% at Air Temp. = 20°C).

3.1.2 Standardized PMV (SPMV)

Gagge et al. [12] in 1986 proposed SPMV as:

$$PMV = \alpha[H_{sk} - h^{'}(T_{sk} - T_o) - E_{diff} - E_{comf}] \tag{3.1}$$

where E_{diff} is the evaporative heat loss caused by diffusion of moisture through the skin, E_{comf} is zero and increases with activity when metabolic rate is greater than 58.2, $h^{'}$ is transfer coefficient, T_o is the operative temperature of the environment, T_{sk} is skin temperature, H_{sk} is heat exchange at the skin surface with environment. α is a sensitivity factor, decreased rapidly from 0.06 during rest to a relatively constant level of 0.03 after resting metabolic rate doubles.

3.1.3 Standard Equivalent Temperature (SET)

ASHRAE defined Standard Effective Temperature (SET*) Index, defined as the equivalent dry bulb temperature of an i sothermal environment at 50% RH in which a subject, while wearing clothing standardized for activity concerned, would have the same heat stress (skin temperature T_{sk}).

3.1.4 Predicted Percentage Dissatisfied (PPD)

Predicted Percentage of Dissatisfied (PPD) predicts the percentage of occupants that will be dissatisfied with the thermal conditions. It is a function of PMV, given that as PMV moves further from 0, or neutral, PPD increases. The maximum number of people dissatisfied with their comfort conditions is 100% and, as you can never please all of the people all of the time, the recommended acceptable PPD range for thermal comfort from ASHRAE 55 is less than 10% persons dissatisfied for an interior space. The equation for PPD is given as:

$$PPD = 100 - 95e^{[} - (0.3353PMV^4 + 0.2179PMV^2)] \tag{3.2}$$

3.1.5 Universal Thermal Climate Index (UTCI)

Defined by International Society of Biometeorology [13] as an Equivalent Temperature (ET) of an actual thermal condition is the air temperature of the reference condition causing the same dynamic physiological response. The references considered are: relative humidity: 50%, Air Velocity 0 m/s, full shade. The temperature range defined as:

Table 3.1: UTCI Temperature Range

Temp. Range	$> 46°C$	38 to $46°C$	32 to $38°C$	26 to $32°C$	9 to $26°C$	0 to $9°C$	-13 to $0°C$	-27 to $-13°C$	-27 to $-40°C$	$< -40°C$
Label	Extreme Heat Stress	V. Strong Heat Stress	Strong Heat Stress	Mod. Heat Stress	No Thermal Stress	Slight Cold Stress	Mod. Cold Stress	Strong Cold Stress	V. Strong Cold Stress	Extreme Cold Stress

3.2 Works on Estimating PMV

3.2.1 Neural Network

Ferreira et al. [14] applied Radial Basis Function neural network (RBF-NN) in a model-predictive HVAC system considering all the six parameters. The training was done using Levenberg-Marquardt (LM) algorithm. Using 23000 training dataset, maximum and average absolute error turned up to be 0.011 and 0.0025 with 100 testing points.

Chengli et al. [15] used traditional neural network with BP to find training MSE around 0.0008.

3.2.2 Vector Machine

Megri er al. [16] used Support Vector Machine with linear kernel and variants of polynomial kernel to estimate PMV considering all the six parameters required. The cost function used by them was:

$$L(x) = \begin{cases} |PMV - g(x) - \varepsilon, & |PMV - g(x)| \geq \varepsilon. \\ 0, & \text{otherwise.} \end{cases} \tag{3.3}$$

where decision function $g(x)$ is

$$g(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(x, s_i) + b \tag{3.4}$$

where l is the number of support vectors (s_i), and the coefficients α^* and b are determined by quadratic programming. $K(..)$ of the inner product of the nonlinear feature is called kernel function.

3.2.3 Genetic Algorithm

Bingxin et al. [17] considered all the six parameters mentioned previously for describing PMV to apply Genetic Algorithm for training. Three AM-101 environment analyzer were used to get indoor and outdoor data. They used back propagation with the fitness function as :

$$f(X) = \frac{1}{\sum_{i=1}^{n} (t_i - m_i)^2} \tag{3.5}$$

where n is sample number, t_i is sample value, m_i is sample average value.

The Mean Squared Error (MSE) converged to 10^{-5}. They also observed that, Air Temperature had a positive while Air Velocity had a negative correlation with PMV.

3.2.4 Fuzzy Set

Li et al. [6] used Type-2 fuzzy sets neural networks combined with back propagation for error adjustment and Least Square Estimate (LSE) for estimating. They considered only Air Temperature and Relative Humidity, distributed each of them into five T2FS, before applying them to a hidden layer and then LSE. The references for other parameters were:

Metabolic Rate: 69.78 W/m^2

Clothing Factor: 0.7 Clo

Mean Radiant Air Temperature: Same as Air Temperature

Air Velocity: 0.2 m/s

They tuned the parameters' value by BP and observed a RMSE value of around 0.2 for 567 training data samples.

Later Yifan et al. [7] proposed a modified ANFIS model combined with multivariate linear regression for estimating PMV in 2000. Each parameter was distributed into various sets.Specific set of knowledge was incorporated for adding more rules (5 experience based and 33 generated rules) and MATLAB was used to simulate these. They also gave justification of choosing more number of parameters. In one of the variants of their work, without considering human variables, they achieved a RMSE value of 0.065. Considering human variables RMSE value came down to 0.046 for 3200 training data and 600 testing data.

While turning our focus into deep learning modules, there were very few works combining Fuzzy sets and CNN or CNN's application in regression. Although none of them were targeted in estimating PMV.

3.3 Works Using CNN as Regression and/or With Fuzzy Models

3.3.1 Fuzzy-CNN for Handwritten Digit Recognition

Popko et al. [18] combined fuzzy rules with CNN for cases where CNN modules fail to complex written numbers. They had generated a rule database before applying 2 layers of convolutional layer and one hidden fully-connected layer. The output neural values $Y_n^l(x,y)$ of the n-th feature map of the convolutional layer l was calculated as:

$$Y_n^l(x,y) = f\Big(\sum_m \sum_{i=0}^{k-1} \sum_{j=0}^{k-1} \omega_{mn}^l(i,j).Y_m^{l-1}(x+i,y+i) + b_m^l\Big) \tag{3.6}$$

where x, y are coordinates of a neuron inside the feature map;M is the set of feature maps of the previous layer $l-1$ that are associated with the n-th feature map of the layer l; ω_{mn}^l is the matrix of synaptic coefficients (the convolution kernel); K is the size of the receptive field of the neurons of the l-th layer; b_m^l being the bias term for the n-th feature map of the l-th layer.

Recognition accuracy for the test set reached 99.23% for MNIST dataset.

3.3.2 Fuzzy-CNN for Depth Weighting

Moreno et al. [19] used CNN to classify depth of an image by initially fuzzifying its' depth variations and then applying CNN to it. Coupling of convolve layer and max-pooling layer were used 3 times before applying fully connected layers and softmax function. This saw 90.2% accuracy.

3.3.3 CNN for Regression

Zhou et al. [20] combined Recurrent Neural Network (RNN) with CNN to estimate pain intensity from a person's face in a video frame. Given vector sequences of AAM-warped facial images, they used sliding window to obtain fixed-sized input samples for RNN. The best MSE they obtained lied around 1.12.

Chapter 4

FUZZY-CNN ARCHITECTURE

In this work, ANFIS approach is adopted (without any prior knowledge of rules) while the estimation of consequent parameters (a_j) as mentioned in Section 3 is left to CNN layers. Regression using neural networks is a widely practiced approach. In order to estimate the PMV, the five parameters which are considered are: Air Temperature (T_a), Relative Humidity (RH), Air Velocity (V_{air}), Metabolic Rate (Met) and Clothing Factor (Clo). Another comparison study involved Mean Radiant Temperature (T_R) also.

4.1 Pre-Processing

The five parameters and T_R are distributed into multiple fuzzy sets using standard Gaussian Distribution Function as shown in Equation 8:

$$\mu_i^j(x_i) = \exp[-\frac{(x_i - a_i^j)^2}{2(b_i^j)^2}] \tag{4.1}$$

where μ_i^j is membership function for input x_i and rule j; while a and b are corresponding mean and Standard Distribution (s.d) respectively.

- *Air Temperature:* Data is distributed into three fuzzy sets: cold, normal (with more standard deviation i.e. flat/spread curve for the two extreme sets), hot; while hot and cold having moderate s.d. (depicted in Fig. 4.1)

- *Relative Humidity:* Gaussian functions used to split into 3 sets: humid, normal, dry.

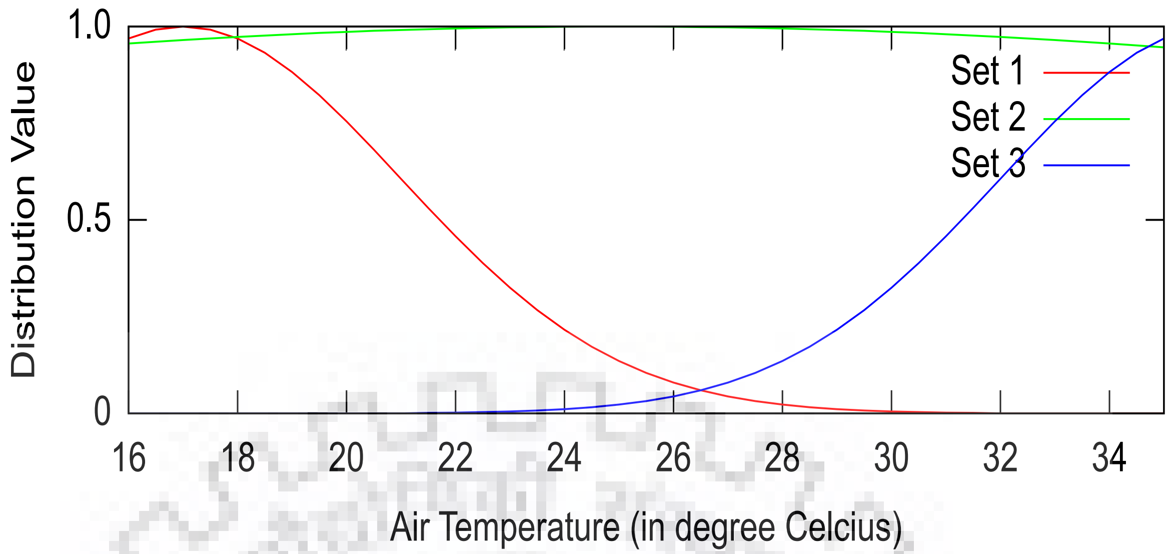

Figure 4.1: Initial Fuzzy Distribution of Air Temperature.

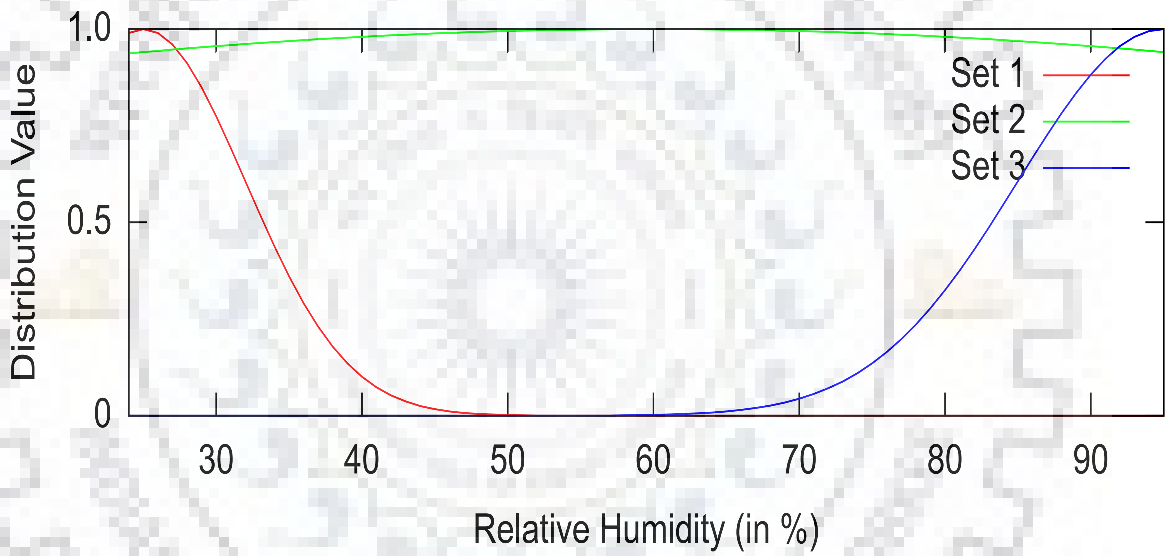

Figure 4.2: Initial Fuzzy Distribution of Relative Humidity.

Very low s.d applied to the two extreme sets while flat curve was maintained for normal one (depicted in Fig. 4.2).

- *Air Velocity:* Similar gaussian distribution is used to divide into three sets: stormy, moderate air flow, almost still air with moderate s.d in two extreme and high s.d in median set (depicted in Fig. 4.3).
- *Mean Radiant Temperature:* T_R is distributed in same way as T_a.
- *Metabolic Rate:* Metabolic Rate is divided into three sets: slow, moderate, active giving moderate set a high variance.

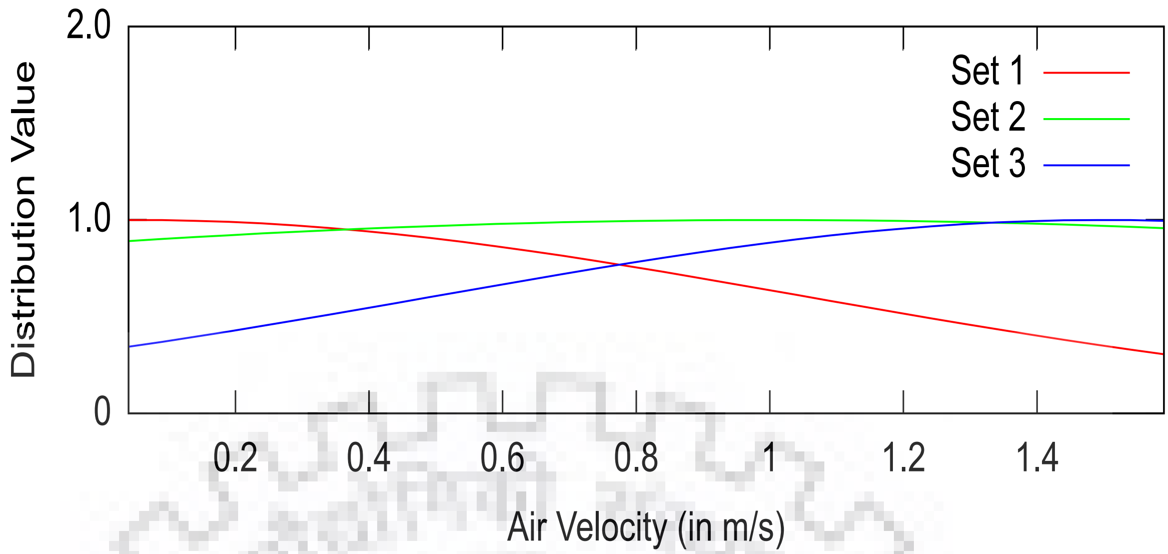

Figure 4.3: Initial Fuzzy Distribution of Air Velocity.

- *Clothing Factor:* Finally clothing rate is divided into three sets heavily clothed, normal and minimal clothing. Heavily clothing was given low variance while moderately clothing set was given high variance.

4.2 Layer Architecture

Initially we have all the five parameters each divided into three fuzzy sets i.e. a total of 15 values. The Fuzzy-CNN architecture consists of five layers as described below and in Fig. 4.4.

- *Layer 1:* Using the pre-processed fuzzified values rule combinations are generated. Each rule is considered to be a tuple of five values (ans six values for the variation where T_R is used) where each value is is corresponding to one parameter's particular fuzzy-set value. Hence we have a total of 243 (729 in case of six-variable) rules. One sample rule j will be:

  If x_1 is $\mu_1^j(x_1)$ AND x_2 is $\mu_2^j(x_2)$ ... AND x_p is $\mu_p^j(x_p)$

  Then output is y

  where x_i are input parameters (total p), μ is membership function. The input variables considered sequentially are: air-temperature, relative humidity, air-velocity, metabolic rate, clothing factor. Combinations are generated in following way: if there are two sets A = $[a_1,a_2]$ and B = $[b_1,b_2]$ there ordered combinations will be =

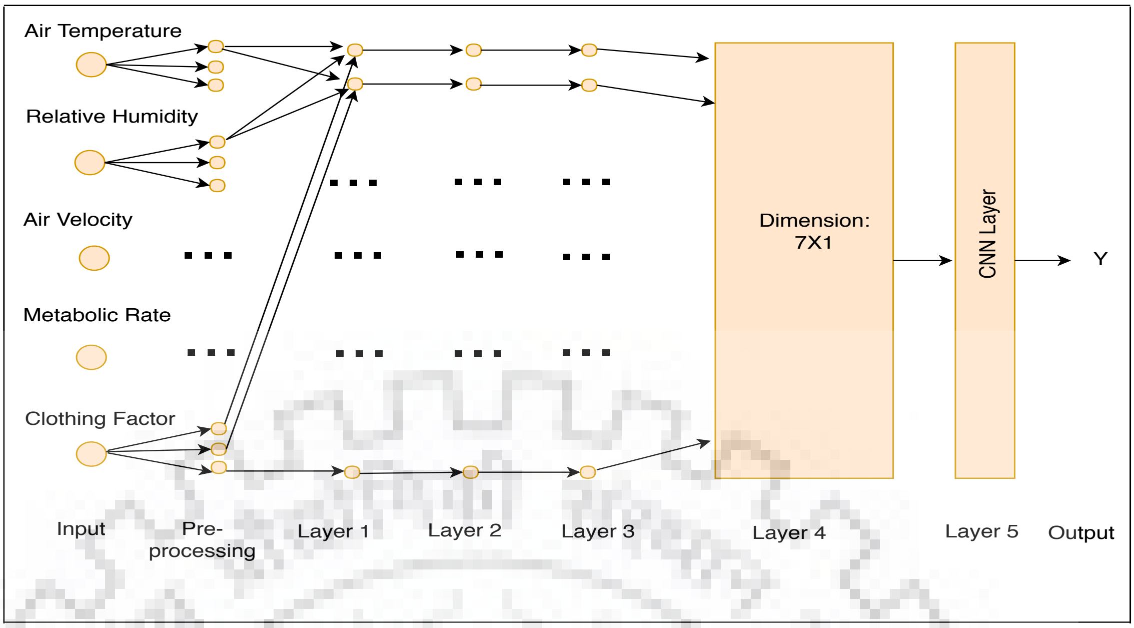

Figure 4.4: Overall Architecture of Fuzzy-CNN.

[(a_1,b_1), (a_1,b_2), (a_2,b_1), (a_2,b_2)]

- *Layer 2:* Each rule values are intra-multiplied in order to get rule-strength (w_j) based on Equation 2.6.

- *Layer 3:* Each rule strength value is normalized ($\bar{w}_i$).

$$\bar{w}_j = \frac{w_j}{\sum_j w_j} \tag{4.2}$$

- *Layer 4:* The output of layer 3 is multiplied with corresponding input data (which was passed as input into Layer 1) embedded with the average of five parameters and 1. This embedding can be regarded as bias term a_0 as in Equation 2.7.

- *Layer 5 (CNN):* In order to get the parameters or to estimate y in Equation 7, deep networks are incorporated. First, generic 3 layer neural network with RMSProp optimizer and learning rate around 0.0005 is used to find y from 243 x 7= 1701 parameters (729 x 8= 5832 for six-variable). Later, it was compared to deep architecture consisting of a 7 x 1 (8 x 1 for other case) convolve layer with one channel and stride

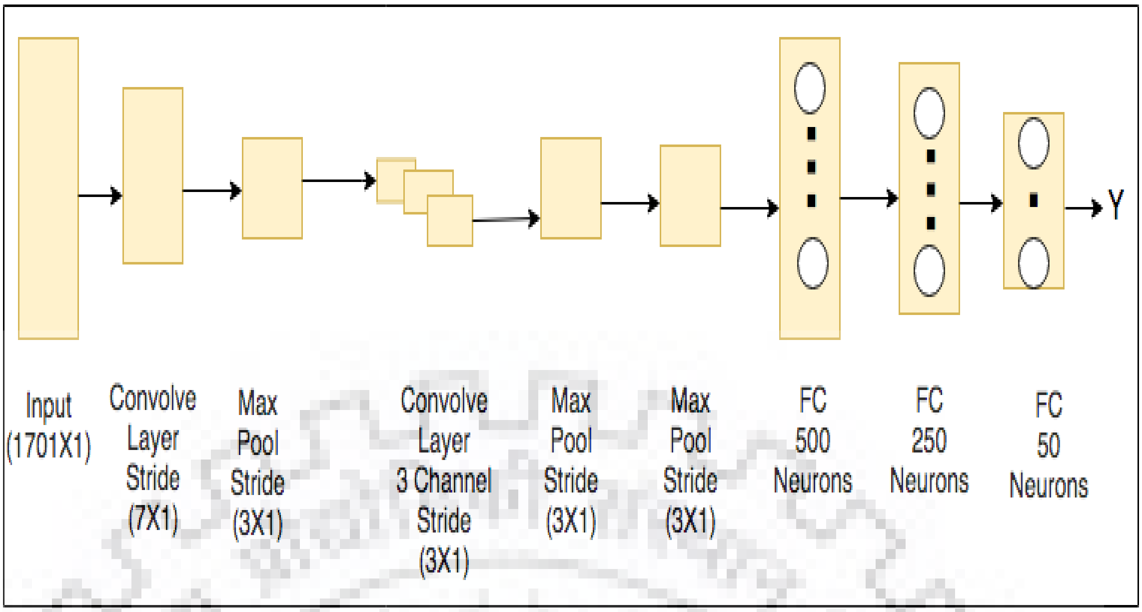

Figure 4.5: Internal Architecture of Layer 5.

of 7 (8 for other case) units, followed by a 3 x 1 max-pool layer and stride of 3 units which is again passed through convolve layer of size 1 x 1, 3 channels and unit stride followed by max-pool same as last one. This was followed by 3 fully-connected layers with 500, 250 and 50 neurons respectively. This entire architecture of layer 5 for 5 variable is in Fig. 4.5.

4.3 Choice of Variables

The Mean Radiant Temperature (MRT) is related to air-temperature according to ISO 7726 standard [21]. Considering MRT as one of input parameters number of rules would grow significantly large (729) and number of consequent parameters reached 729 x 8 = 5832, which is a three-fold increase in terms of parameter estimation. The comparison of results for both 5 and 6 variable cases are revealed in Section . Metabolic rate [22] and clothing factors [23] are un-avoidable as shown by *Yifan et al.* [7]. Air-temperature, relative humidity and air-velocity are maintained as key parameters.

4.4 Input System

For experimenting and analysis, RP-884 was used as reference. The datasets for one NV building by *Dear et al.* [24] and 22 HVAC buildings by *Cena et al.* [25] were combined as entire dataset to be used. The former one was obtained from wet equatorial climate of Singapore, in the year 1991. The latter one was from hot arid region of Kalgoorlie-Boulder, Australia for both winter and summer seasons in 1998. The Singapore and Australian winter and summer datasets had 584, 625 and 589 samples respectively, totaling 1798 samples; out of which around 1400 samples were used for training and 400 for testing randomly at runtime.

The parameters used in experiment were in range as follows:
Air Temperature: 16.7 °C to 36.1 °C.
Relative Humidity: 24.54 % to 97.82 %.
Air Velocity: 0.043 m/s to 1.567 m/s.
Mean Radiant Air-Temperature: 16.82 °C to 32.81 °C.
Metabolic Rate: 0.772 Met to 2.58 Met. ($1Met = 58W/m^2$)
Clothing Factor: 0.045 to 1.57

Chapter 5

SIMULATION RESULTS AND ANALYSIS

As setup, Python 3.2 and tensorflow, numpy were used. Before considering neural network linear regression and polynomial regression (degree 3) were applied for 5 parameter version. Root Mean-Squared Error (RMSE) value reached around 0.08 and 0.04, respectively. Initially, considering only 3 fully connected traditional neural networks appended to layer 4 of our ANFIS model, the best Root Mean-Squared Error (RMSE) value reached around 0.8 with train and test data set in similar way. Fuzzy-CNN model separated into train and test set as discussed, it reached a good RMSE value of around 0.018 for 5 parameters and around 0.08 considering T_R on the testing data, considering no prior knowledge were used in both cases. ANFIS with no prior knowledge with multivariate regression reached best RMSE of 0.04.

The error plot showed in Fig. 5.1 shows relative error between actual and predicted values of PMV with respect to Air Temperature for first 100 test samples.

Table 5.1: Error Analysis

Approach	**RMSE**
Fuzzy-CNN with 5 parameters	0.02
Fuzzy-CNN with 6 parameters	0.08
ANFIS with Prior Knowledge	0.04

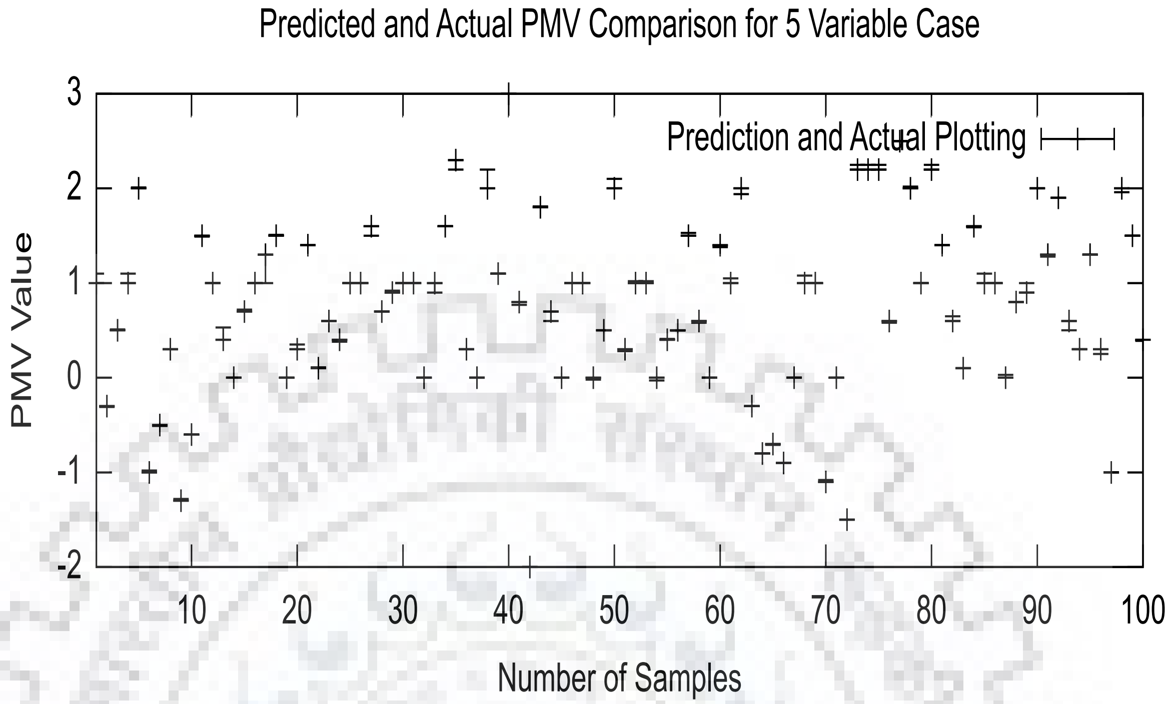

Figure 5.1: Samplewise Comparative Study of Predicted and Actual PMV Values

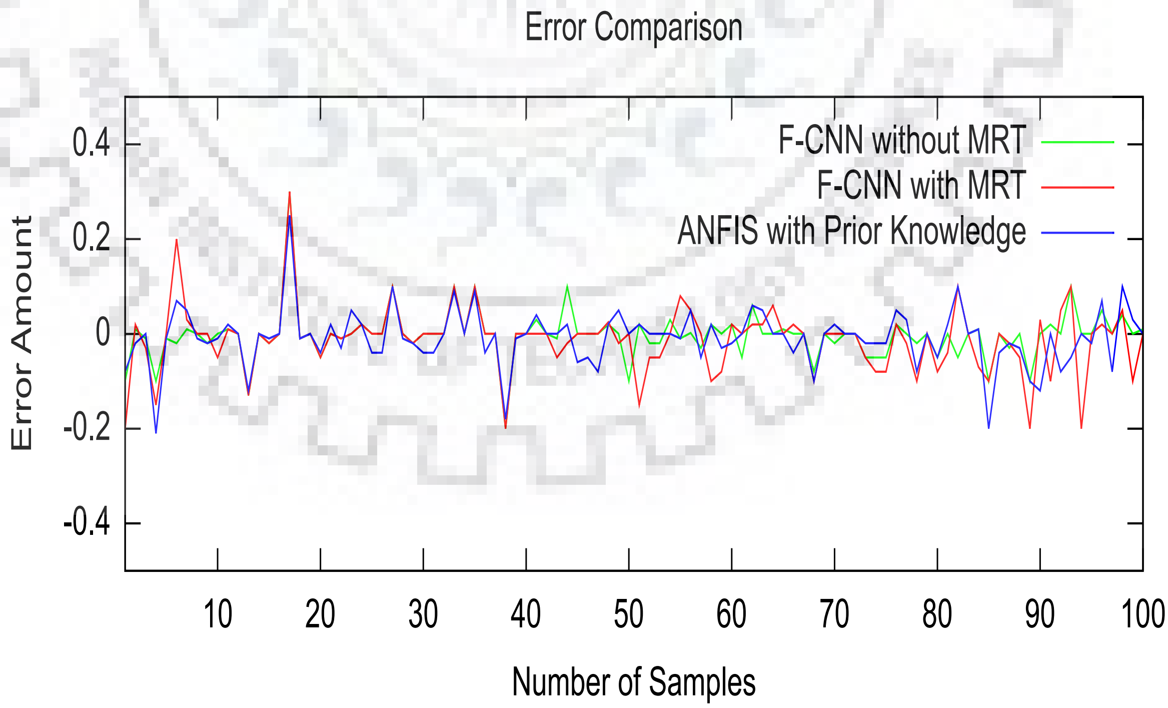

Figure 5.2: Samplewise Comparative Study of Relative Error of Approaches

Fig. 5.2 represents amount of error of each of samples predicted for both the approaches in this work and ANFIS with prior knowledge. This comparison is depicted in Table 5.1.

The consideration of Mean Radiant Air Temperature reduces the accuracy by a large extent. It is observed that RMSProp was able to converge slowly but more efficiently (global minima ≤ 0.019) for both 5 and 6 parameter versions while Gradient Descent converged quickly but with higher global minima (≥ 0.021). Learning rate was maintained as 0.0005

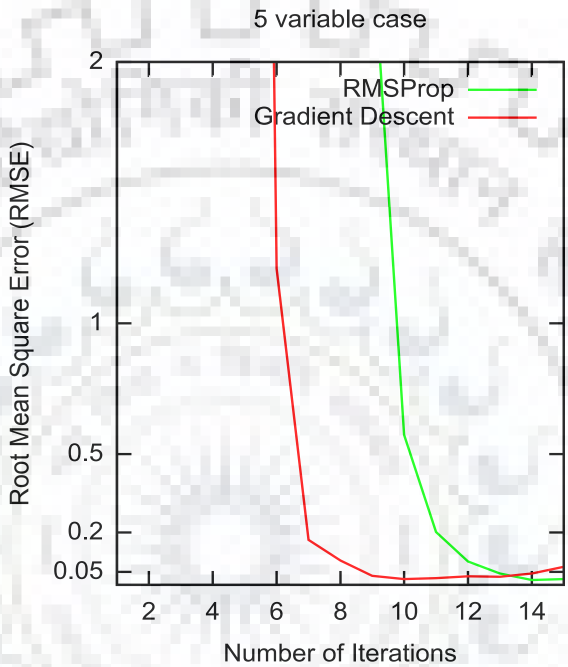

Figure 5.3: RMSProp and GD Optimizer Comparison for 5 Parameter Case

and batch size was maintained as 5, increasing the batch size did not have significant effect on global minima except, it converged more slowly.

As seen from Fig. 5.3 and 5.4 the RMSE values have a specific trend with respect to iterations for both the five and six parameter case. Also, without the last pooling layer, the best RMSE value did not reach below 0.04 for 5 variable case. Fig. 5.3 and 5.4 shows how the RMSE converges against iterations for our approaches with both optimizers while Fig. 5.5 , 5.6 and 5.7 shows finally tuned fuzzy set value for three parameters.

5.1 Discussions

As discussed in Chapter 4, convolutional layer performs dot product and hence results in downsampling of input. In our 5 variable case, input dimension is $1701 \times 1 \times 1 \times 1$ (height

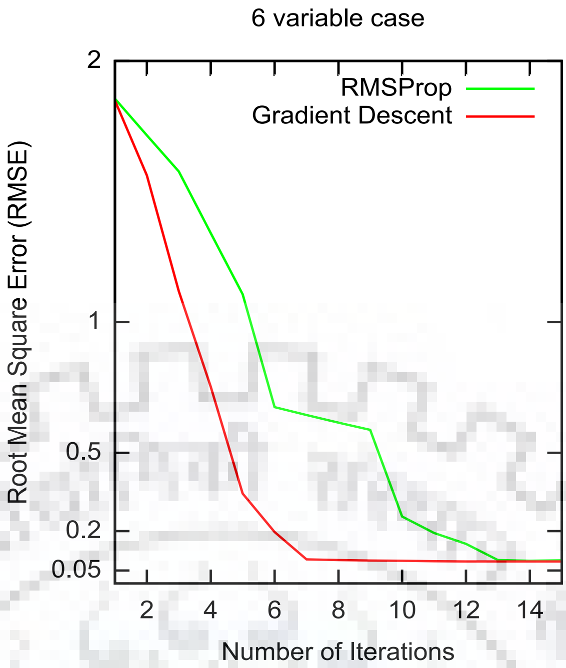

Figure 5.4: RMSProp and GD Optimizer Comparison for 6 Parameter Case

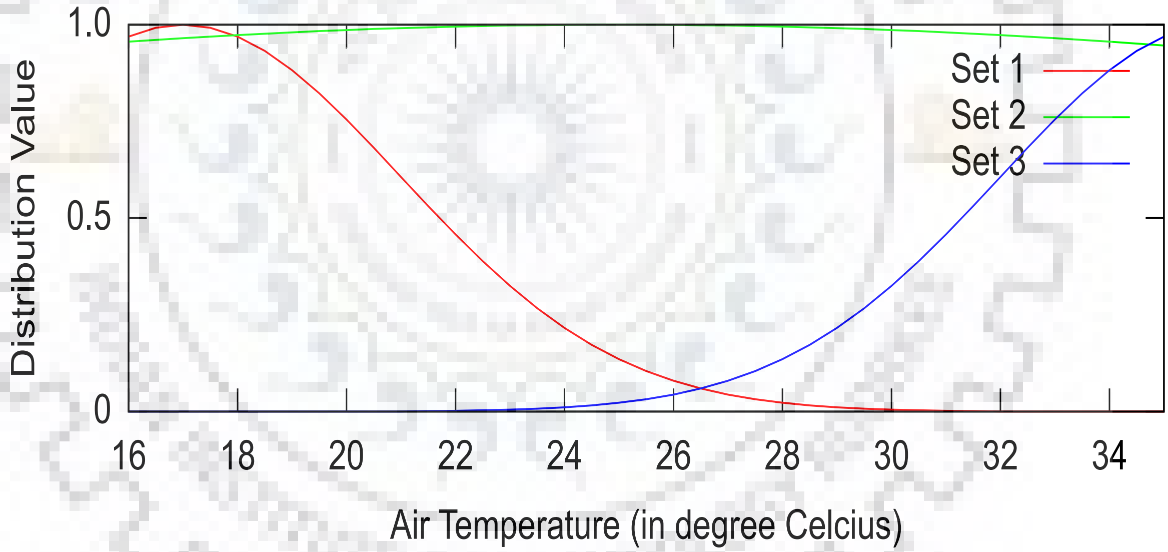

Figure 5.5: Tuned Fuzzy Distribution of Air Temperature.

x width x depth x channels). After convolving with 7 x 1 sized filter with stride of 7 x 1 x 1 x 1 we are reducing each expanded rule value into the a singular value meaning, we now deal with 243 parameters. Similar to this, the six-parameter version would reduce to 729 values. This value can be considered related to the normalized rule strength from layer 3. This reduction is similar to layer 4 to 3 (backward) but in a different way. Max-pooling with window size 3 x 1 x 1 x 1 downsamples every 3 consecutive value into a singular one (maximum one). Before normalizing in layer 3, in layer 2, every 3 consecutive rule

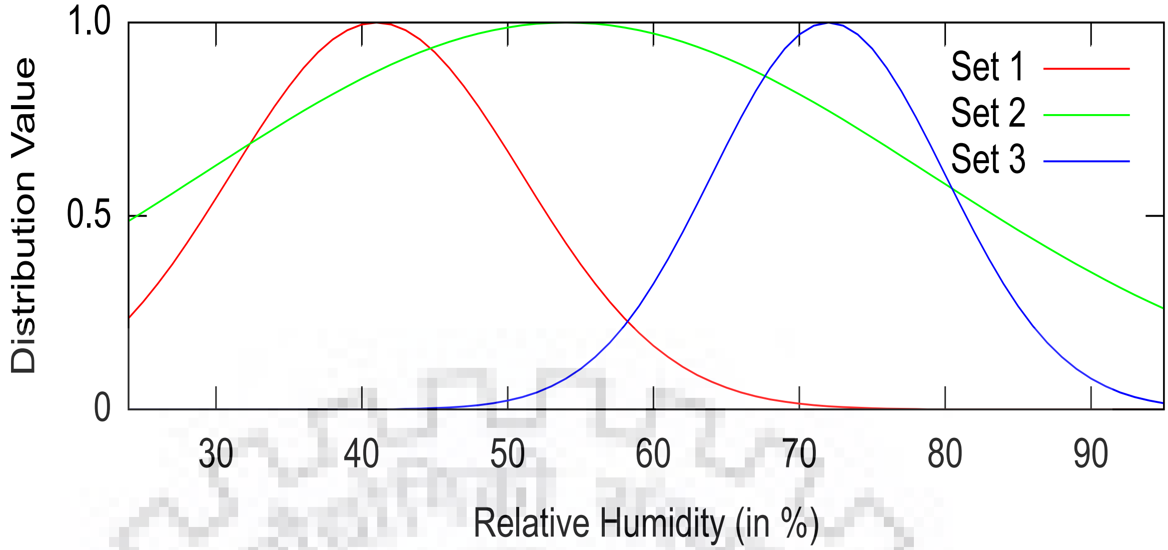

Figure 5.6: Initial Fuzzy Distribution of Relative Humidity.

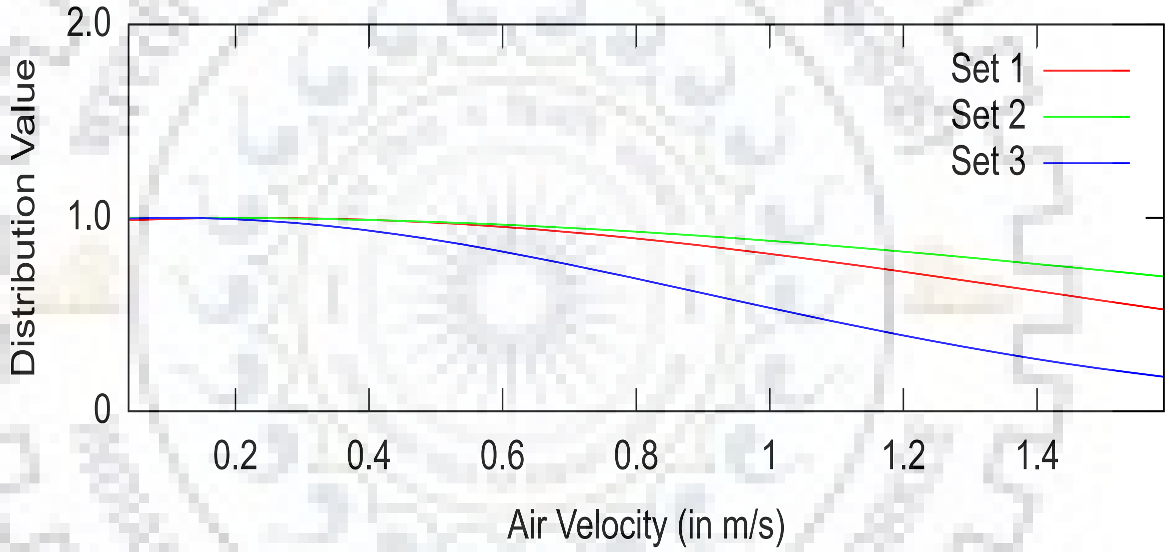

Figure 5.7: Tuned Fuzzy Distribution of Air Velocity.

strength differed only in terms of clothing rate (Clo) membership function values. This pooling step is kept max, not average, as optimizing would be less complex. Now we are reduced to 81 values and 243 for six-variable case. The next convolve layer performs dot product with each value obtained in last step but adds 3 channels to it making it 81 x 3 sized data. Reshaping it we get 243 x 1 shape again. Again max-pooling reduces it to 81 values (243 for other case) which imply getting rid of effect of the clothing factor parameter. One more layer of max pooling of similar dimension and stride reduces it to 27 values, this can be considered as neutralizing metabolic rate's (Met). Adding layers after it affected results and time to train. The second convolve layer was added to make an increase in number of parameters to optimize and pass different value to second pooling layer.

Few fully-connected layers that are added to it as discussed start with having neurons almost 20-fold the number of parameters (27 x 19 $\approx$ 500). Weights and biases of these FC layers are initialized as random normal values.

Chapter 6

CONCLUSIONS AND FUTURE SCOPE

The consideration of mean radiant temperature (T_R) reduces the estimation accuracy; also T_R is related to Air Temperature (T_a) which might effect in re-consideration of same parameter. One can conclude that CNN efficiently deduces the inter-dependencies of the parameters and their impact in estimating the final PMV values. As PMV is a widely used comfort index metric, CNN does a good work in choosing parameters and estimating it.

This work could as well be extended by considering Boltzmann Machine, RBF Networks or suitable deep learning framework in combination with ANFIS or as a standalone system. This requires sufficient and extensive experimentation and analysis.

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DISSEMINATION FROM DISSERTATION

Submitted Papers

Manuscripts Under Preparation

1. **Anirban Mitra**, Arjun Sharma, Sumit Sharma and Sudip Roy, “*Fuzzy Convolutional Neural Network Based Thermal Comfort Index Estimation*", To be submitted to the 27th International Conference on Artificial Neural Networks (ICANN), May, 2018.