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APPLICATION OF A NEUROFUZZY MATHEMATICAL MODEL IN THE DEVELOPMENT OF A LOCAL OVEN DESIGN

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ABSTRACT

This paper presents a contribution on the development of a neurofuzzy mathematical model that aids in capturing and analyzing the various parameters in oven design. The oven was designed specifically for domestic and commercial baking operations. The neurofuzzy methodology was used to regulate the oven baking temperatures to acceptable standards. Particular use was made of neurofuzzy model since it is an improvement on the process design. The work was motivated by the need for a more reliable and easily understandable methodology that guides decision makers in making correct decisions in a timely manner. The results obtained demonstrated that it is feasible to apply the model in practice.

Keywords: Oven design, Neuro-fuzzy model, baking operation, temperatures

INTRODUCTION

An oven is an enclosed box-like structure designed and constructed for the purpose of generating heat for cooking food, baking bread, meat pie, drying paints and organic enamels, baking founding cores and low temperature treatment of metals. Ovens are of different types, shapes, and sizes And may include electric, gas, kerosene, saw dust and wood ovens. Electric oven makes use of electricity as a source of heat generation; gas oven uses cooking gas, while the wood oven makes use of coal to generate its heat energy (Cook and Harman, 1991).

Most ovens consist mainly of the body, the lagging material, the heating element, the control system and the protective devices. The lagging material is the material that is fixed between the inner walls and the outer walls that reduce the rate of heat loss by radiation. The common lagging materials include, fibreglass, sawdust and asbestos (Metcalfe, 1979). According to Wildi (1969) if a resistor is heated in a thermally insulated chamber, most of the heat generated is conserved and can be applied to a wide variation of heating processes (Taylor, 1983).

Today, oven designs, manufacture and maintenance have gone through major changes due to advances in technology and strategies. The use of soft computing techniques such as data mining, fuzzy logic, artificial neural networks, genetic algorithms and neurofuzzy techniques, which have been recognized as improved tools for solving problems in the servicing industry, are gradually being recognized in the field of design and manufacture (Wu and Harris, 1997; Shahin *et al.*, 2003; Olunloyo *et al.*, 2004; Meesad and Yen, 2000). While fuzzy logic has been widely used for tracking uncertainty, its integration with artificial neural networks is a recent development in capturing the individual weaknesses in fuzzy logic and artificial neural networking (Harris *et al.*, 1995; Ivan *et al.*, 1998). The offspring of this marriage, neurofuzzy, has been applied for numerous tasks: in the reinforcement learning of traffic signal control (Bingham, 2001); for identification of autonomous underwater vehicles (Bossley *et al.*, 1999; Lee *et al.*, 2001); in real time modelling and control (Harris *et al.*, 1995); for robust parameter estimation (Ivan *et al.*, 1998), and in vibration monitoring (Meesad and Yen, 2000). Therefore, there is a need to use and develop a practical approach such as the neurofuzzy approach, which can deal with uncertainty or vagueness in system parameters.

This paper presents a contribution on the development of a neurofuzzy mathematical model that aids in capturing and analyzing the various parameters in oven design.

MATERIALS AND METHODS

Parts and operations of the machine: The oven consists of the main body, the wire gauze, the heating element and the coil holder. Although these components are considered important, the prominent component is the heating element, which generates the heat required to keep the baking temperatures at acceptable standards. The heating element was carefully selected to suit the design specifications. A nickel–chrome heating element with standard wire gauge of 26 and resistance of 6.5Ω/m was selected because, nickel–chrome has a low oxidation and a high melting point.

Design analysis; total baking time: The total time it takes to bake a material in the oven was given by the equation

$T_b = t_c + t_f$

where

$$t_c = \frac{W_i - W_c}{Amfc} \text{ and } t_f = \frac{1}{Am} In\frac{f_c}{f}$$

$$\therefore \quad T_b = \frac{1}{Am}\left[\frac{W_i - W_c}{f_c} + In\frac{f_c}{f}\right]$$

where

T_b = total baking time (sec)
W_i = initial moisture content of material
W_c = critical moisture content
f_c = free moisture content at critical condition
f = free moisture content
m = ratio of rate of drying per unit area to moisture content
A = area of exposed surface (mm^2)

Heat emitted by surface: The heat emitted by the surface as given by Einshaw (1983) was

$$P = KA\left(T_1^4 - T_2^4\right)$$

where

P	=	heat radiated (w)
A	=	surface area of the body (m^2)
T_1	=	absolute temperature of the body (K)
T_2	=	absolute temperature of the surrounding object (k)
K	=	constant or radiation efficiency.

The rate of heat flow: The rate of heat flow through a body or material being baked inside the oven was given as

$$P = \frac{A(T_2 - T_1)\lambda}{d}$$

$$P = \frac{A\delta T\lambda}{d}$$

$$P = \frac{1}{d}A\delta T\lambda$$

$$P = A\delta T\lambda d^{-1}$$

$$P_{max} = \sum A\delta T\lambda d^{-1}$$

This was summarised as follows:

$$\sum A\delta T\lambda d^{-1} \left\{\begin{matrix} = \\ > \\ < \end{matrix}\right\} P_{max}$$

where

P = Power (heat) transmitted (w)
λ = thermal conductivity of the body (W/m°C)
A = surface area of the body (m^2)
δT = ($T_2 - T_1$) = difference of temperature between opposite faces (°C).
d = thickness of the body (m).

The neurofuzzy methodology that was applied in the current design combined the inherent attributes of fuzzy logic and artificial neural networks. Fuzzy logic has the attribute of capturing uncertainty and imprecision. However, the advantage of artificial neural networks in specifying more precisely the nature of uncertainty in a network was utilized. The starting point of the

procedure for applying a neurofuzzy methodology was to define the input parameters that were used in the process towards obtaining the output.
The basic inputs into the neurofuzzy model were mainly the surface area of the body, difference of temperature between opposite faces, thickness of the body and thermal conductivity of the body.
The output that could be obtained from the modeling was basically three-fold: optimistic, pessimistic, and normal. The optimistic output refered to a situation that was desired, the normal output related to results that came out on the average, while the pessimistic output was the undesired level of output. In mathematical terms, these outputs were stated as follows:

$$(\sum A\delta T\lambda d^{-1} - P_{max}) = H \text{ (Optimistic)}$$
$$(\sum A\delta T\lambda d^{-1} - P_{max}) = L \text{ (Pessimistic)}$$
$$(\sum A\delta T\lambda d^{-1} - P_{max}) = N \text{ (Normal)}$$

RESULTS AND DISCUSSION

The components of fuzzy logic control model for the development of local oven design with membership functions were presented in table 1.

Table 1: Relationship between fuzzy output and membership function

Level	Interpretation	Fuzzy Output	Linguistic Variables
1	Optimistic	Positive	$(\sum A\delta T\lambda d^{-1} - P_{max})$
2	Most Likely	Zero	$(\sum A\delta T\lambda d^{-1} - P_{max})$
3	Pessimistic	Negative	$(\sum A\delta T\lambda d^{-1} - P_{max})$

The degree of relationship between fuzzy output and membership function ranged from 0 to 1.0. The next stage in the modelling was to evolve the structure of the neurofuzzy application (Figure I). The structure was made of three distinct parts namely input, layers, and output. The inputs were denoted by 'X'. This could be X1, X2 and X3 for the framework shown in figure I.

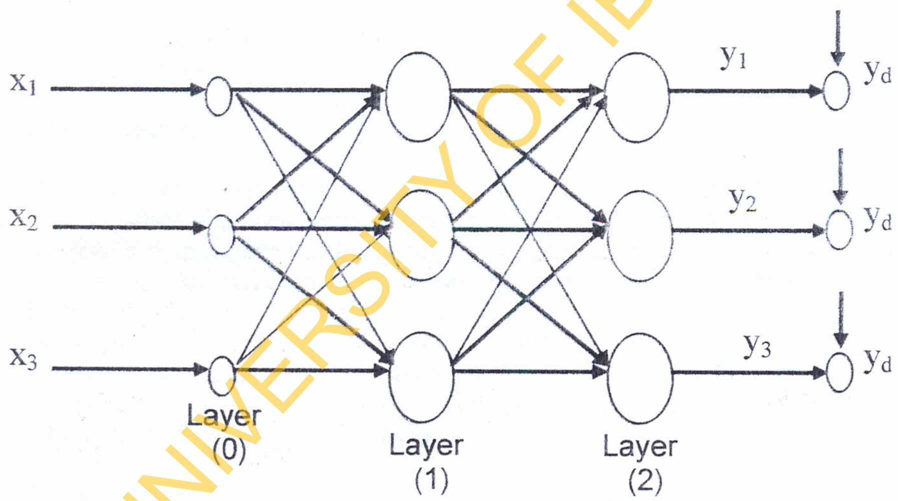

Fig. I: The Neurofuzzy structure for the oven design problem

Each of these 'X' values may represent different inputs such as bump height, distance between two consecutives bumps, the spring constant of the vehicle, the damping constant of the vehicle, etc. As such, the number of 'X' values may be equivalent to the number of input parameters that were being considered. In this case, the structure of the diagram would be more complicated than what is illustrated above.
The second division of the neurofuzzy structure consists of layers. Layers are interconnections between the input and output neurons. In this particular defined instance, three layers were specified and included layers 0, 1, and 2.
The next segmentation of the neurofuzzy structure was the output. This was represented by 'y'. Specifically, there were y1, y2, and y3. The output had to be refined in order to obtain the desired

output. The refined output was referred to as the desired output, 'yd'. The simplified form of neurofuzzy model was presented in figure II.
However, a number of rules guide the implementation of the neurofuzzy model for the case considered here. These were referred to as system operating rules. The definitions of these rules were as follows:

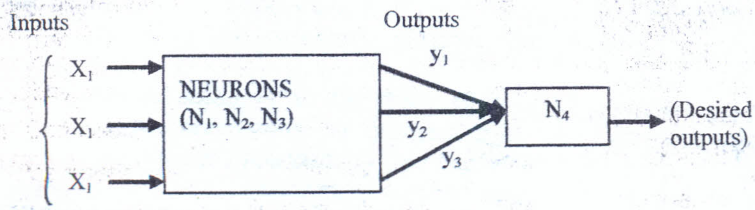

Fig. II: Layout of the neurofuzzy model

System operating rules: INPUT # 1: ("Input," High (H), Low (L), Normal (N))

INPUT # 2: (Getting High (GH), Getting Low (GL), Getting Normal (GN)) CONCLUSION: ("Output", Optimistic (H), Pessimistic (L), Normal (N))

INPUT #1: System Status

Input: $(\sum A\delta T\lambda d^{-1} - P_{max})$

H = High, L = Low, N = Normal

GH = Getting High, GL = Getting Low, GN = Getting Normal
OUTPUT: Conclusion and System Response
OUTPUT: H = Op, L = Nil, N = Nil
In applying the rules, the following 'IF-THEN' statement applies:

IF $(\sum A\delta T\lambda d^{-1} - P_{max})$ = H, AND (Σhde – Vmax) remains H, THEN output = Op

IF $(\sum A\delta T\lambda d^{-1} - P_{max})$ = L, AND (Σhde – Vmax) remains L, THEN output = Nil

IF $(\sum A\delta T\lambda d^{-1} - P_{max})$ = N, AND (Σhde – Vmax) remains N, THEN output = Nil

It should be noted that the optimistic situation (Op) is the state where the maximum baking pressure is lowest.

CONCLUSION

The level of temperature attainable with the unit wss found to be quite suitable for both domestic and commercial baking operations. In particular, the neurofuzzy model is used as an approach in capturing the imprecision and uncertainty involved in quantifying the parameters of oven design. We have developed a neurofuzzy approach in the design of oven baking temperature for domestic and commercial purposes. The approach is adopted in order to improve on the use of fuzzy logic, which attempts to capture imprecision and uncertainties. The fusion of artificial neural network and fuzzy logic has been scientifically proven to produce better results than the independent usage of fuzzy logic or artificial neural networks. This contribution may therefore be judged as beneficial to system design.

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