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Research Article

Sensor-Aided Localized Capsule-Cooling Using Neural Networks for Energy-Efficient Refrigeration

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Abstract

Sensor-aided localized capsule-cooling technique is a unique refrigeration process where sensors precisely capsulate the location of an item(s) on a shelf of a fridge and hence direct the governing artificial intelligence to take suitable action. Here the sensors are used to locate the objects and the designed smart system (neural network) activates the corresponding ductlines to cool the object. Here neural network system opens the gate(s) and tilts the angle to allow the flow of cool air through the ductlines. Then the orifices, which fall in the virtual “Hot Region”, the domain that the active sensors had created almost immediately on sensing an obstruction, are opened. The orifices and sensors are arranged in a series on the lower wall of the ductlines to allow flow of air in the downward direction. These open orifices facilitate the direct hitting of cool air on the target-item and hence create a cold block within a fridge, instead of cooling the entire fridge uniformly, to keep the singular item refrigerated. This mode of operation offering selective cooling, rather than the conventional uniform one, is useful in saving energy, as the region then needed to be cooled is reduced significantly. A detail structural and theoretical explanations along with graphical analysis clearly elucidate the effective working of this mechanism under practical circumstances is given here. In this paper neural network is used for capsule cooling for energy efficient refrigeration

Keywords: capsule-cooling, energy-efficient refrigeration, proximity-sensor, target-localization Neural Networks

1. Introduction

Early nineteenth century saw the making of the refrigeration machine or the refrigerator as it is widely called, and over the last two centuries it has slowly become the indispensable part of regular household. A refrigerator is a cooling appliance comprising of a thermally insulated compartment and a heat pump which by chemical or mechanical means, transfers heat from it to the external environment and hence cooling the contents to a temperature below ambient. Several techniques have been employed over the years for efficient cooling without harming the environment. This paper on analyzing the various drawbacks of the conventional mechanism of refrigeration will introduce a new and unique “localization’ technique, which can make the system a lot more energy sustainable. This new system aims at “Conservation of energy” and through a sensor-aided target-localization technique achieves that efficiently [2]. Through detail theoretical analysis and successful diagrammatic system-virtualization, the viability of the new system has been elaborately discussed in this paper.

2. Back Ground

In the modern world, where conservation of energy has become a major concern in formulating any process or devising any plan, this paper attempts to introduce a unique sensor-aided localization-technique for a highly energy-efficient refrigeration process, easily adaptable in the modern fridge that is generally used in normal household, provided they are subjected to the required modification. Generally the cool air from the compressor is thrown into the thermally insulated compartment, where the things needing refrigeration are kept. The cool air circulates through out the whole insulated compartment maintaining a particular cycle (convection) and maintains uniform temperature through out. Hence, every corner of the fridge is cooled almost equally and hence all goods inside the compartment are taken care of [10]. Now a situation is considered, where out of the 3 or 4 shelves, there is only one container of food in one of the shelves. Even then, according to the general method of refrigeration, the entire fridge gets cooled uniformly and in the process this lone container in the entire fridge is also cooled. But this special case witnesses a high amount of redundancy. The energy or power required to cool the entire fridge is far greater than the power needed to cool a particular region within the fridge, where the container is kept. But regional cooling within a fridge is not possible until and unless the fridge knows or is fed with the information regarding the placement of the container. Physically feeding the information is definitely not a viable option because if there is multiple numbers of containers at different corners of the fridge, then mentioning

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the placement of all of them with respect to a reference coordinate system is a very complicated task. Hence the system should provide that information to the fridge.[3] This process of localization of the target(s) [in this case the target(s) is (are) the container(s)] and informing relevant data to the fridge regarding the region(s) needed to be cooled immediately has been explained in this paper in details.

3. Mechanism

In Figure 1, the detail working of the entire mechanism has been shown diagrammatically. It indicates the sensor-aided cooling technology by the creation of the "Hot Region". Generally in a fridge, shelves are found to be in the form of grill to facilitate free and unobstructed current of air through out the compartment. Here in this paper, a similar structure is followed. But here each strand of grill, ductline (Figure 2.a) as it will be called in this paper, is actually a duct or pipe-line to carry cold air to different parts of the fridge. That is, each fine line (as shown in the diagram) is actually a hollow cylinder to make space for the flow of air through them to the entire fridge.[4] Now each ductline is fitted with distance measuring or proximity sensors and holes or orifices alternatively, as shown in Figure 2.b.

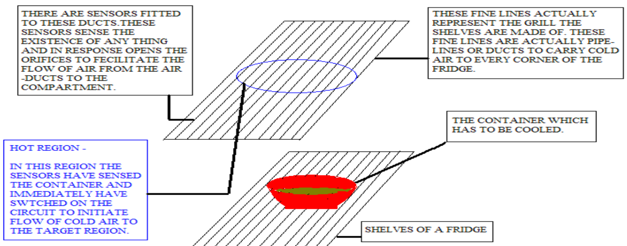

Fig 1..Mechanism of sensor-aided localized cooling.

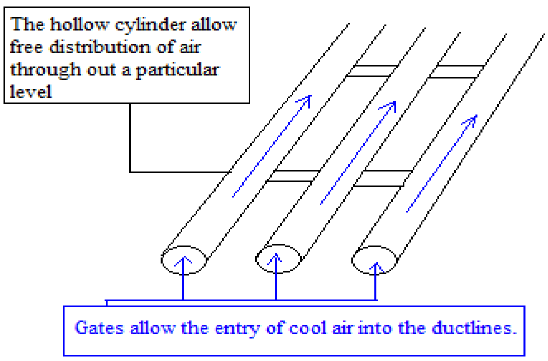

Fig. 2. Ductlines

3.1 Duct line

Generally in a fridge, shelves are found to be in the form of grill to facilitate free and unobstructed current of air through out the compartment. Here in this paper, a similar structure is followed. But here each strand of grill, ductline (Figure 2) as it will be called in this paper, is actually a duct or pipe-line to carry cold air to different parts of the fridge. That is, each fine line (as shown in the diagram) is actually a hollow cylinder to make space for the flow of air through them to the entire fridge.[5] Now each ductline is fitted with distance measuring or proximity sensors and holes or orifices alternatively, as shown in Figure 3

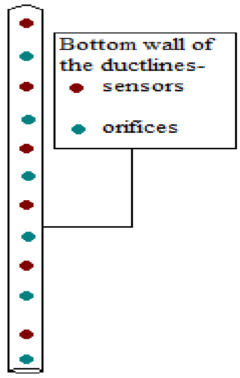

Fig 3. Arrangement of sensors-orifices

3.2 Working of sensors

Here distance measuring or proximity sensors are needed to be used to sense the existence of any item on the shelf. These devices typically transmit a short burst of ultrasonic sound toward a target, which reflects the sound back to the sensor. The system then measures the time for the echo to return to the sensor and computes the distance to the target using the speed of sound in the medium. These devices work at ultrasonic frequencies (>20 kHz) and hence background noise do not significantly effect the efficiency of its working [9]. The microphones and loudspeakers used to receive and transmit the ultrasonic sound are called transducers. Most ultrasonic sensors use a single transducer to both transmit the sound pulse and receive the reflected echo, typically operating at frequencies between 40 kHz and 250 kHz. Thus it can concluded that as soon as the echo reaches the transducer back, the attached microprocessor interprets it to be an obstruction and immediately opens the gates to allow flow of air through the ductline and also opens the orifices to allow the flow of air directly on the entity (obstruction) and hence concentrating on a virtually created domain.

4. Neural Networks

A neural network is a concept in computing which is loosely modelled on the structure and operation of the brain. It consists of a number of simple processing units `cells' or `nodes' connected together into a layered net-like structure. When a given set of cells (the inputs) are stimulated, the signals are passed through the network from node to node and finally exit the network through another set of simplified nodes (the outputs). The computational elements or nodes in the hidden and output layers are generally nonlinear. The simple node sums 'N' weighted inputs and passes the result through a nonlinearity known as activation or transfer function. The node is characterised by an internal threshold or bias and by the type of non-linearity. There are three common types of non-linearities: hard limiters, threshold logic elements and sigmoidal nonlinearities. More complex nodes may include temporal integration or other types of time dependencies and more complex mathematical operations than summation.[7] Neural network models are characterized by the network topology, node characteristics, and training or learning rules. These rules specify an initial set of weights and indicate how weights should be adapted during use to improve performance. The most commonly used type of neural network is the Multi-Layered Perceptron (MLP) network MLPs are widely used as modelling tools and have been successfully applied for the prediction and modelling of multi-variable non-linear systems. It has been claimed by many researchers that a MLP network with a single hidden layer can approximate any non-linear function with arbitrary accuracy. A three-layer perceptron with one layer of hidden units is shown in Figure 1. For MLP networks, training is normally achieved through back-propagation learning. Supervised learning involves comparing the output of a network exposed to specific input with the desired output and changing the weights of the network to achieve a proper mapping. This is done by first stimulating the input nodes with a specific pattern and letting the network propagate this input through the layers. The output of the network is then compared to the desired output (i.e. the output expected for that particular input pattern). The error is then back-propagated through the network, changing the internal weights along the way to produce a better match between the network predictions and the `real' data.. To facilitate this process a number of techniques can be used which include the *delta-rule* method. The figure 3 shows that the sensors here are used as inputs and the orifice angles are used as the outputs.

4.1 Back Propagation Algorithm

The objective of supervised training is to adjust the weights so that the difference between the network output *Pred* and the required output *Req* is reduced. [8] This requires an algorithm that reduces the absolute error, which is the same as reducing the squared error, where

Network Error = Pred - Req = E

These outputs are multiplied by the respective weights ($W_{1B}...W_{nB}$), where W_{nB} is the weight connecting neuron *n* to neuron *B*. For the purpose of this illustration, let neuron 1 be called neuron *A* and then consider the weight W_{AB} connecting the two neurons. The approximation used for the weight change is given by the delta rule:

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial W_{AB}}$$

where η is the learning rate parameter, which determines the rate of learning, and

$$\frac{\partial E^2}{\partial W_{AB}}$$

is the sensitivity of the error, E^2, to the weight W_{AB} and determines the direction of search in weight space for the new weight $W_{AB(new)}$

In order to minimise E^2 the delta rule gives the direction of weight change required

From the chain rule,

$$\frac{\partial E^2}{\partial W_{AB}} = \frac{\partial E^2}{\partial I_B} \frac{\partial I_B}{\partial W_{AB}} = O_A$$

since the rest of the inputs to neuron *B* have no dependency on the weight W_{AB}.

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial I_B} O_A$$

and the weight change of W_{AB} depends on the sensitivity of the squared error, E^2, to the input, I_B, of unit *B* and on the input signal O_A.

5. Gates And Orifices

As soon as the sensors go active in a particular region(s) of a shelf(s), the concerned neural network model processes the interrupt signal and switches on the circuit that opens the gates to facilitate the flow of air into the duct lines of that particular shelf(s). As mentioned earlier the sensors and orifices are placed in series alternatively on the bottom-wall of the duct lines. [9] Hence the sensors that have sensed the obstruction create a virtual “Hot Region”. In that hot region, all the orifices are opened to allow the cold air, that was till now being duct-borne to be released through the orifices and allowed to hit directly on the item (target).

5.1 Surround Cooling

Generally in a refrigerator surround cooling i.e cooling from all sides is a very important feature and very effective in keeping items in good condition. Here in this process, cool air hits the target from the roof (floor of the shelf above) and hence sideways cooling starts a while later, when the entire region cools down. But to escalate the rate of cooling and also provide the experience of surround cooling, two additional concepts are defined over here – Inner Area and Outer Area, as shown in Figure 4. Inner Area is nothing but the “Hot Region” defined earlier. Outer Area comprises of two or three orifices more on all sides, besides the ones directly falling in the “Hot Region”. This orifice instead of releasing or spraying cool air perpendicularly does that at a particular angle, (inwards) targeting the concerned item.

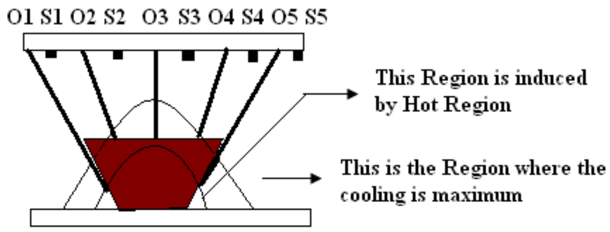

Fig. 4. Hot region and the region where cooling required

The Figure 4 above shows the orifice and sensors. Here O1,O2,O3,O4,O5 indicate the five orifices and the S1,S2,S3,S4,S5 indicates the five corresponding sensors. In the figure 5 below the object is at the center and the sensors S2,S3,S4 identifies the object and hence the orifices O2,O3,O4 are perpendicular at 90 degree (which is 50% of 180 degree and hence the decimal value is 0.5) to give maximum cooling to the object. O1 is at an angle of 72 degree (0.4 x 180) and the orifice O5 is at angle of 108 degree (0.6x180). When the object is moved on the left corner as shown in figure 6 the S1,S2,S3 identifies the object and the corresponding orifice angle is 90 degree (0.5x180) and the orifice O4 and O5 are at an angle 108 (0.6x180) and 126 degree (0.7x180) to give maximum cooling. In figure 7 when the object moves to the right side the S4 and S5 identifies the object and hence the orifice O4 and O5 are at an angle of 90 degree (0.5x180) and the other orifices O3, O2 and O1 are at an angle of 72 degree (0.4x180), 54 degree (0.3x180) and 36 degree (0.2 x180) respectively. Here we use the decimals 0.2,0.3,0.4,0.5 etc as the neural network can use (0-1) values for training.

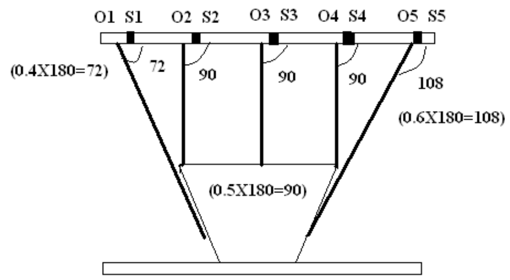

Fig . 5. Object at the Center

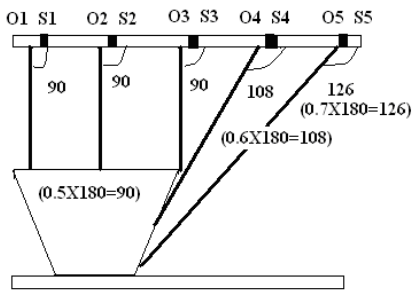

Fig. 6. Object at the left corner

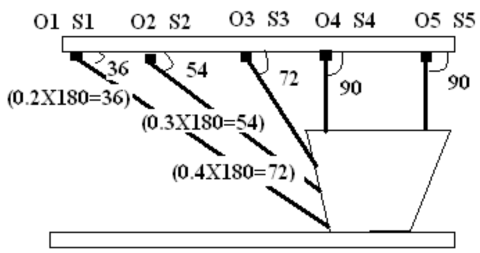

Fig.7 Object at the right corner

The table below shows the state of the sensors and the angle of tilt for orifice (represented in decimal for example 90 degree is represented as 0.5 as it is the 50% of 180degree). Here in Table1 S1,S2,S3,S4,S5 indicates the state of sensor and O1-O5 indicates the angle of tilt in orifice (for example (0.4 indicates that the angle of tilt is (0.4x180= 72 degree). The figure below shows the training for each output and the corresponding comparison output between the actual value and the predicted output from the neural network. Figure 8 shows the neural network training for the output angle of orifice 1 (O1) and figure 9 shows the actual output and the predicted output. For example when the sensor input is 0 1 0 1 0 (11-decimal value) the actual corresponding angle of tilt is 0.4, 0.5, 0.4, 0.5, 0.6 (72,90,72,90,108 degrees) and the predicted output from the neural network gives 0.4027, 0.5013, 0.3976, 0.5141, 0.6075. Hence in figure 9 for decimal value 11 the actual outputs are marked in blue and the predicted output in green. Similarly the graph comparison is also given for the other four orifices. The figures (10-13) correspond to orifices O2, O3, O4, O5.

Table 1: Sensor state and the corresponding angle of tilt created by the user.

Ti					State of Orifice (Angle of Tilt)				
S1	**S2**	**S3**	**S4**	**S5**	**O1**	**O2**	**O3**	**O4**	**O5**
0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0.1	0.2	0.3	0.4	0.5
0	0	0	1	0	0.2	0.3	0.4	0.5	0.6
0	0	0	1	1	0.2	0.3	0.4	0.5	0.5
0	0	1	0	0	0.3	0.4	0.5	0.6	0.7
0	0	1	0	1	0.3	0.4	0.5	0.4	0.5
0	0	1	1	0	0.3	0.4	0.5	0.5	0.6
0	0	1	1	1	0.3	0.4	0.5	0.5	0.5
0	1	0	0	0	0.4	0.5	0.6	0.7	0.8
0	1	0	0	1	0.4	0.5	0.3	0.4	0.5
0	1	0	1	0	0.4	0.5	0.4	0.5	0.6
0	1	0	1	1	0.4	0.5	0.4	0.5	0.5
0	1	1	0	0	0.4	0.5	0.5	0.6	0.7
0	1	1	0	1	0.4	0.5	0.5	0.4	0.5
0	1	1	1	0	0.4	0.5	0.5	0.5	0.6
0	1	1	1	1	0.4	0.5	0.5	0.5	0.5
1	1	0	0	0	0.5	0.5	0.6	0.7	0.8
1	1	0	0	1	0.5	0.5	0.3	0.4	0.5
1	1	0	1	0	0.5	0.5	0.4	0.5	0.6
1	1	0	1	1	0.5	0.5	0.4	0.5	0.5
1	1	1	0	0	0.5	0.5	0.5	0.6	0.7
1	1	1	0	1	0.5	0.5	0.5	0.4	0.5
1	1	1	1	0	0.5	0.5	0.5	0.5	0.6
1	1	1	1	1	0.5	0.5	0.5	0.5	0.5

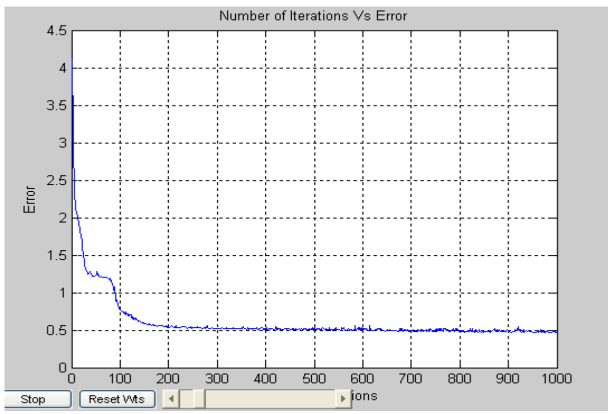

Fig. 8. No of iterations Vs O1

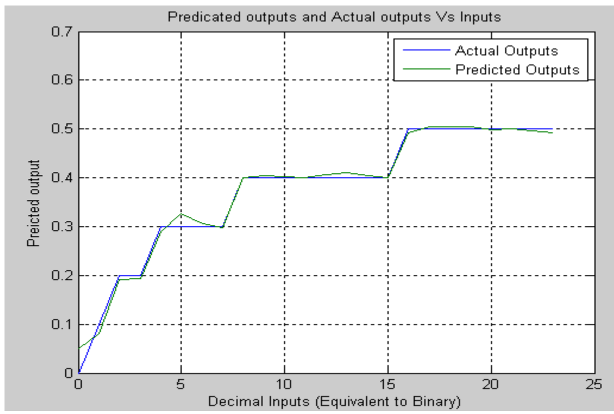

Fig .9. Predicted o/p, actual o/p comparison for O1

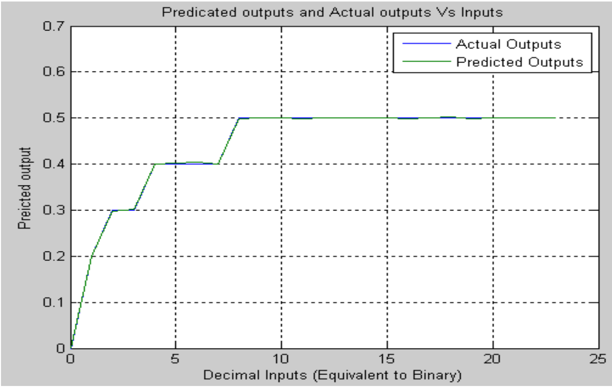

Fig. 10. Predicted o/p, actual o/p comparison for O2

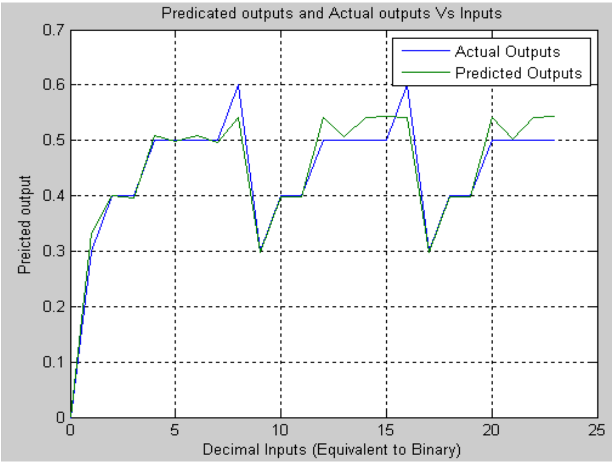

Fig. 11. Predicted o/p, actual o/p comparison for O3

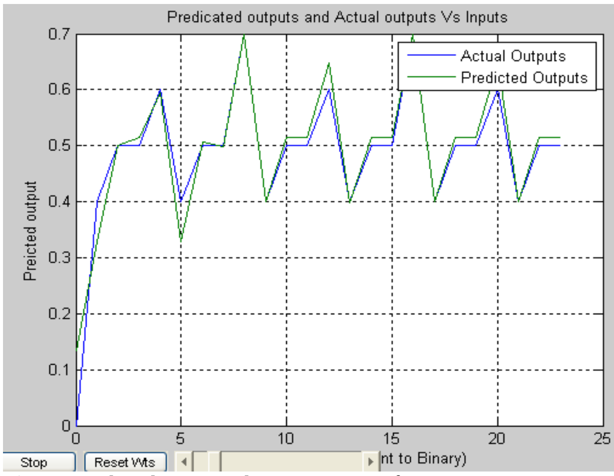

Fig .12. Predicted o/p, actual o/p comparison for O4

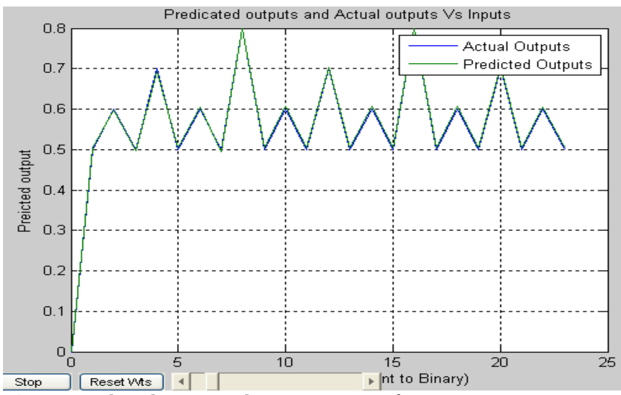

Fig. 13. Predicted o/p, actual o/p comparison for O5

5.2 Neural Network Analysis

As per the above discussion neural network is used to train the network for digital ultrasonic sensor inputs and the tilt angle of the orifice outputs, and it is seen that the neural network responds well with the new learned matrix. There are very minute negligible errors in the tilt angles of O3 and O4. Now this neural network model can well be used for optimized energy efficient refrigeration.

6. Conclusion

In this paper with the help of theoretical analysis, the working of a new concept of refrigeration has been explained, which saves a lot of energy through the application of an additional circuitry and slight modification in the structure of conventional fridge components. The synchronized functioning of the sensors and neural system can efficiently perform effective surround cooling to a given item(s), specially, when majority of the fridge is empty. This entire mechanism of sensor-aided localized capsule-cooling provides an alternate mode of operation and in the process reduces power consumption considerably. Neural Networks is used to identify the five digital outputs of sensors and depending on the various positions the tilt angles are send to orifices for optimize cooling.

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