FROST PREDICTION ON EVAPORATOR COILS OF SUPERMARKET DISPLAY CABINETS USING ARTIFICIAL NEURAL NETWORKS

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Defrosting in supermarket refrigeration systems is normally controlled by a preset time cycle with most display cabinets timed to defrost every 6 hours. It is widely acknowledged that timed defrost may cause a number of unnecessary defrost cycles and this reduces the energy efficiency of refrigeration systems as well as the accuracy of temperature control of the cases. This paper investigates the possibility of modelling the amount of frost on the coil by using neural networks and proposes a demand defrost method based on it which should overcome the disadvantages of other demand defrost approaches.

INTRODUCTION

Frost forms on evaporator coils by the water vapour in the air condensing and freezing when the surface temperature of the coil falls below 0°C. A small amount of frost may improve the heat transfer performance of the coil by increasing the surface area and surface roughness which induces increased turbulence (1). However, significant frost accumulation deteriorates the coil performance by reducing the air flow and thereby the refrigerating capacity of the evaporator. Maintaining the store humidity at low levels, and using air curtains to prevent penetration of humid store air into the display cases, reduces the rate of frost formation on display case evaporators to some extent, but does not eliminate it completely due to the disturbance of the air curtain by shoppers and staff loading up the display case. Consequently, frosting is a major problem in retail refrigeration systems and evaporators need to be actively defrosted periodically to maintain system performance and temperature control in the display cases.

The most commonly used defrost methods in display cases are hot or cool gas defrost and electric defrost. In electric defrost, the thermal energy to melt the ice is provided by an electric strip heater which is situated across the face of the coil. During defrost the refrigerant supply to the display case is switched off, the electric heater is switched on, and the evaporator fans blow air which is heated by the strip heater through the coil, melting the ice from the coil surface. This method of defrost can be implemented on both conventional, single compressor refrigeration systems, and multiplex refrigeration systems which are now widely used in large retail stores. These consist of three or four compressors connected in parallel, providing flexibility in system capacity control and maintenance.

Another advantage of multiplex refrigeration systems over conventional systems is that they allow both hot and cool gas defrost techniques to be implemented. The former involves the circulation of hot gas from the compressor discharge manifold directly to the display cases whereas the latter utilises cooler gas from the liquid receiver. The cool or hot gas condenses in the evaporator, releasing heat which melts the ice from the coil. During this process the evaporator fans are switched off to prevent water carry-over from the coil. The liquid refrigerant produced in the display cases during defrost is piped back to the liquid manifold of the compressor pack for distribution to the other display case circuits. Multiplex refrigeration systems supply refrigerant liquid to a number of display cases which are piped in parallel. For this reason, the number of display cases which can be defrosted simultaneously is limited to avoid starvation of the compressors and system shut-down due to low suction pressure.

The refrigeration systems in most large stores are monitored and controlled by a central network supervisor. The supervisor controls all the individual case and cold room controllers, compressor pack controllers, condenser controllers and monitors pressure and temperature at various points in the system. Defrost can be initiated by the supervisor or individual case controllers. In most cases, for simplicity of operation and maintenance, defrost is initiated at fixed time intervals. Defrost scheduling of the display cases and the number of defrost cycles per day are set during store commissioning. Defrost, whether gas or electric, is normally terminated when a fixed defrost time elapses or when the case evaporator air-off temperature reaches a set value, whichever is sooner.

Defrosting involves the application of heat to the coil in order to melt the frost and this penalises refrigeration system performance due to the fact that during the defrosting process energy is used while producing no useful cooling. Furthermore, during the defrost cycle the case and thus the product temperature rises above the set limits for normal operation. A demand defrost control system which defrosts the evaporator coils when sufficient frost has formed to adversely affect their performance would lead to both better temperature control and considerable energy savings.

ENERGY UTILISATION DURING DEFROST

Accurate determination of the energy consumption during the defrost cycle would require comprehensive instrumentation to measure the power consumption of the refrigeration packs during defrost. Although it will be useful to carry out such an exercise, this is beyond the scope of the present paper. It is interesting, however, to make an estimate of the energy consumed during defrost and this can be based on the following assumptions:
Number of defrost cycles during a 24 hour period: 4
Energy input during the defrost cycle: 3 kW (based on electric defrost)
Average defrost time: 10 minutes

Assuming an average price of electricity of £0.04/kWh, for a large chain of retail food stores having approximately 30,000 display cases, the total annual costs for defrost will be in the region of £500,000. This analysis does not include the extra energy that will be required for the temperature recovery of the case after the defrost cycle. Higher defrost frequency and longer defrost cycle duration will increase further the cost of defrosting.

A considerable opportunity therefore exists to apply more sophisticated defrost control strategies to both save energy and improve temperature control.

DEMAND DEFROST

A number of demand defrost techniques have been applied over the years which include: air pressure differential sensing across the evaporator; sensing the temperature difference between the air and the evaporator surface; fan power sensing; variable time defrost based on relative humidity and air differential across the coil (2, 3, 4).

More recent methods include defrost initiation by measuring the ice thickness through monitoring the resonant frequency of an acoustic oscillator installed on the evaporator, measuring the thermal conductivity of ice (5), using photo optical systems (6), and fibre optic sensors to detect the presence of ice (7). Cost and simplicity of use is a very important factor since the number of display cases in a modern supermarket may range from to 40 to 150.

Use of Artificial Neural Networks

The authors of this paper are currently carrying out investigations to quantify the energy consumption during frosting and defrosting and determining the effects of the various operating parameters such as refrigerant temperature, coil design and surface temperature, air temperature and humidity, air velocity etc. on the rate of frost formation and the amount of frost accumulation on display case evaporator coils.

They have proposed the use Artificial Neural Networks to analyse the monitored data on line and predict the performance of the coil. The amount of frost on the coil would be determined indirectly as a function of the monitored parameters (8).

Neural networks differ from traditional simulation approaches in that they are trained to learn solutions rather than being programmed to model a specific problem. They are used to address problems that are intractable or cumbersome to solve with traditional methods. A Neural Network consists of a number of processing elements (neurons), each of which have many inputs, but only one output. In a typical network there are three layers of neurons i.e. input layer which receives input from the outside world, hidden layer or layers which receive inputs from the input layer neurons and output layer which receives inputs from hidden layers and passes its output to the outside world and in some cases back to preceding layers. The strength of the network lies in the interconnections between the neurons which is modified during training. The training is done by exposing the network to a specified data set of information and applying a training algorithm to enable the network to produce the desired output.

Although the amount of frost accumulation could be determined from empirical correlations available in the literature, namely references (9) and (10), this determination is time-consuming and therefore of very little use in real-time operation. On the other hand, the relationship between the amount of frost accumulation and the refrigerant and air temperatures and pressures as well as space temperature and relative humidity could be learned by a Neural Network. Once training has been achieved the Network could then combine the outputs of the various temperature and pressure sensors to give an on-line estimate of the amount of frost. The Neural Network, in this case would be a “soft sensor”. This is similar to “sensor fusion” where a neural network is employed to an array of sensors that may exhibit non-linear behaviour, to extract linear measurement of a hidden quantity or to produce an estimate of their correlation. Successful application of the `soft sensing' technique has been reported in the biotechnology field where it has been used to determine biomass by its effect on temperature, oxygen, water and carbon dioxide levels. Similarly, the rate of frost formation will be determined by its effect on temperature and pressure parameters.

It is expected that it will be possible to implement the ANN based system on the existing store monitoring and control systems without considerable difficulty. It is envisaged that the system will require mainly software modifications with only minimum additional instrumentation.

EXPERIMENTAL TEST FACILITY

The experimental results of this investigation were obtained using two display cabinets in the laboratory served by a mini multiplex system compressor pack. One of the cabinets was instrumented with thermocouples and pressure transducers while the second cabinet acted as an extra load to facilitate hot or cool gas defrost.

The display cabinet tested was an 8 ft dairy cabinet (Figure 1) with operating temperature of between $0^{o}C$ - 3°C and cooling capacity of 3.7 kW. The refrigerant (R22) flow rate was measured using a Coriolis mass flow meter. Temperatures and pressures of the refrigerant were measured at five points in the system using thermocouples and pressure transducers. The power consumption of the compressors was recorded using a power transducer. The display cabinet and the coil were fitted with thermocouples on the surface. The operation of the system was controlled by a standard Supermarket controller board. A computer, along with data-acquisition module and software was used to record the various parameters at regular intervals.

FIELD TEST DATA

Along with the data collected in the laboratory, a supermarket was also instrumented to record additional parameters, namely the amount of condensate collected after defrost along with the space conditions and operating pressures and temperatures.

Timed defrost assumes a worst case scenario, such as in midsummer, when the moisture content in the supermarket is high. This means that during winter, when the moisture content of the air is lower, unnecessary defrosts of the cabinets are carried out.

The difference between the summer and winter conditions is illustrated in Table 1. It can be seen that in winter the relative humidity in the store is much lower than the average relative humidity in the summer, 25% and 40% respectively, whereas the internal temperature between the isles is approximately the same, 17.7 ^{o}C and $16.7^{o}C$ respectively. The lower internal humidity in winter results in a much lower rate of frost formation with each 6 hour defrost cycle giving 2.5 litres of condensate compared to 5.1 litres of condensate in the summer. This indicates that defrost frequency could be halved in winter without significantly affecting the display case performance.

Table 1: Defrost data from a supermarket

Parameter	August 1996	November 1996
Internal Humidity	40	25
External Humidity	80	86
Internal Temperature	16.7	17.7
External Temperature	14.3	6.7
Amount of Condensate(lt.) per defrost	5.1	2.5

LABORATORY TEST RESULTS AND DISCUSSION

Table 2 shows results obtained from preliminary work carried out in the laboratory. Using the space temperature, relative humidity and the number of hours of cooling a neural network was trained to learn the relationship between these parameters and the amount of condensate obtained after defrost.

Figure 2 shows the amount of condensate collected during defrost as a function of space temperature and humidity for 6 hours of operation between defrost cycles. It can be seen that frost accumulation is a multivariate non-linear function. In practice of course, the rate of frost formation will be a function of a large number of other parameters, including the air velocity over the coil, the refrigerant temperature etc. The figure 2 demonstrates the principle, however neglects the effects of the other variables and concentrates only on store ambient temperature and humidity.

A three layered neural network with three input nodes, seven hidden nodes and one output node was used to learn the above function. The architecture of the network with input and output variables is shown in Figure 3. The predicted output and the training targets for the Network are shown in Figure 4. The correlation obtained was 0.94 which indicates a good prediction of frost formation by the Network.

Figure 5 shows a comparison between actual and predicted results of defrost condensate for 8 tests. The results of these tests were not incorporated in the sample used for the training of the Network, confirming that a trained network can be a good predictor of the quantity of frost on an evaporator coil.

To fit a 3rd order polynomial with three input variables and one output variable to the same data at least 27 data points are required in order to ensure that the adaptive parameters (the coefficients of the polynomial) are well determined. On the other hand, a Neural Network could be trained with available discrete data. The importance of neural networks lies in the way in which they deal with the problem of scaling with dimensionality. Generally, these models represent non-linear functions of many variables in terms of superposition of non-linear functions of a single variable, which might be called ‘hidden functions’ (also called hidden units). The key point is that the hidden functions are themselves adapted to the data as part of the training process, and so the number of such functions only needs to grow as the complexity of the problem itself grows, and not simply as the dimensionality grows. The number of free parameters in such models for a given number of hidden functions, typically only grows linearly, or quadratically, with the dimensionality of the input space, as compared with the d^M growth for a general Mth-order polynomial, where d is the number of input variable.

Table 2: Experimental results obtained in the laboratory

Test No.	Hours of cooling	Space Temperature °C	Relative Humidity %	Condensate collected (lt.)
1	2	13.8	63.7	2.6
2	3	13.8	62.8	3.8
3	3	13.6	64.2	4.5
4	3	20.2	66.3	6.7
5	4	13.6	56.3	4.85
6	5	22.3	34	3.65
7	5	18.4	37.2	6.5
8	5	15.1	51.8	6.5
9	6	19.1	34.7	3.2
10	6	22.9	38.5	7.5
11	6	21.9	57.4	9.3
12	6	20.1	66.3	8.9
13	6.3	12.9	45.3	4
14	6.4	14.1	62.1	6.5
15	7	15	50	7.2
16	16	14.7	61	10.4

CONCLUSIONS

Defrost of supermarket refrigeration systems which is performed on a timed basis consumes excess electrical energy. Defrosting of display cases also disturbs the temperature control of the case resulting in temperatures which exceed the design temperature over a significant time period.

The energy consumption during the defrost process can be reduced using more advanced defrost initiation and termination techniques based on demand rather than timed defrost.

Although a number of different demand defrost strategies have been proposed in the past, none has found wide acceptance in the food retail refrigeration industry due to poor reliability and high capital cost.

This paper proposes a new demand defrost technique based on Artificial Neural Networks. ANNs will allow the monitoring of a large number of parameters simultaneously and the prediction of the rate of frost formation based on the combination of the effects of a number of these parameters. This should eliminate unnecessary defrosts and will allow prioritisation of the display cases in terms of their defrost requirements.

Preliminary results show that Neural Networks can be used to estimate the amount of frost formation on the coil in terms of the amount of condensate obtained after defrost, based on space temperature, relative humidity and hours of cooling.

Further work is being carried out to quantify the effects of frost formation on operating parameters such as refrigerant pressures, refrigerant temperatures, air temperatures, air velocity and coil surface temperatures in order to determine indirectly from such measurements the rate of frost formation on the coil.

REFERENCES

1. Stoecker, W.F., 1957, "How Frost Formation on Coils affects Refrigeration Systems", Refrigerating Engineering, 65(2), 55.

2. Heinzen, R.A., 1988, "How adaptive Defrost maintains Refrigeration System efficiency", Australian Refrigeration, Air conditioning and Heating, 12.

3. Ciricillo, S.F., 1985, "Heat pump de-icing/controlling for energy conservation and costs", Clima 2000, Congress on heating, ventilation and air conditioning, Copenhagen, 87.

4. Muller, E.D., 1975, "A new concept for defrosting refrigeration plants", Kalte, 28(2), 52.

5. Llewelyn, 1984, "A significant advance in defrost control", Int. J Refrigeration, 7(5), 334.

6. Woodley, C.B.C, Aug 1989, "Saving on the defrost", Air conditioning and Refrigeration News, 62.

7. Paone, N., and Rossi, G., 1991, "Fiber-optic ice sensors for refrigerators", Proc of SPIE, 1511, 129.

8. Datta D., Tassou S. A. and Marriott D., "Demand Defrost of Supermarket Refrigeration System", Proc, CIBSE National Conference, Eastbourne, 1995.

9. O'Neal, D.L., and Tree, D. R., 1985, "A review of Frost Formation in Simple Geometries", ASHRAE Trans, 91(2B), 267.

10. Crawford, R.R., Mavec, J.P., and Cole, R.A., 1992, "Literature survey on recommended procedures for the selection, placement, and type of evaporators for refrigerated warehouses", ASHRAE Trans, 98(1), 500.

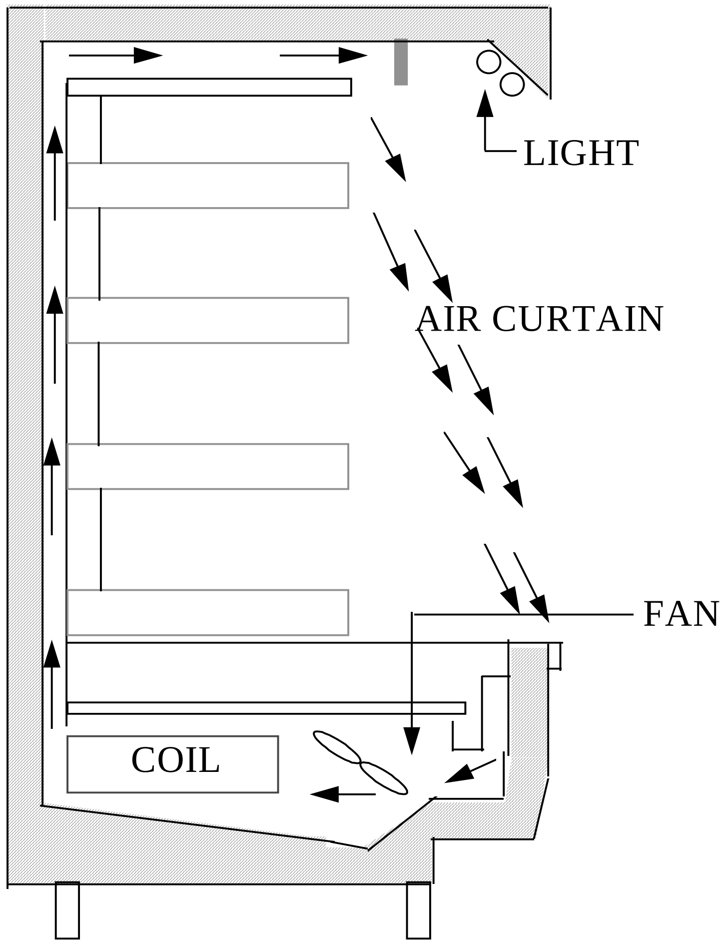


Figure 1: A typical vertical multideck Display Cabinet.

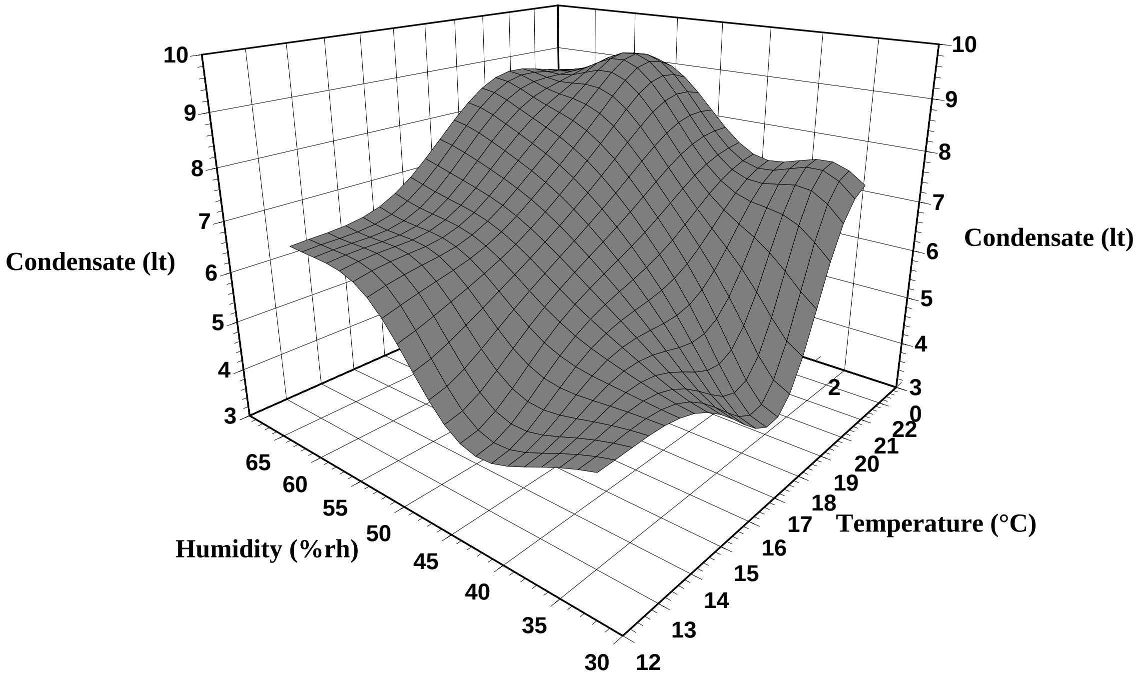
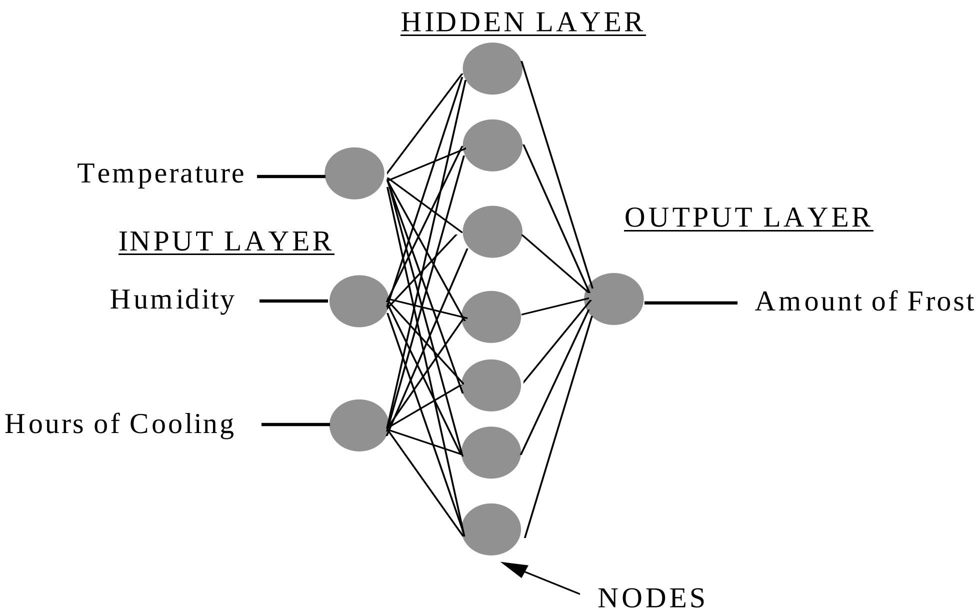


Figure 2: Surface Interpolation for the amount of condensate at varying temperatures and humidities for 6 hrs of cooling.



Number of layers = 3
Input layer nodes = 3
Hidden layer nodes = 7
Output layer node = 1
Transfer function = Sigmoid
Training Algorithm = Backpropagation
Correlation = 0.94

Figure 3: Neural Network Architecture used in this application.

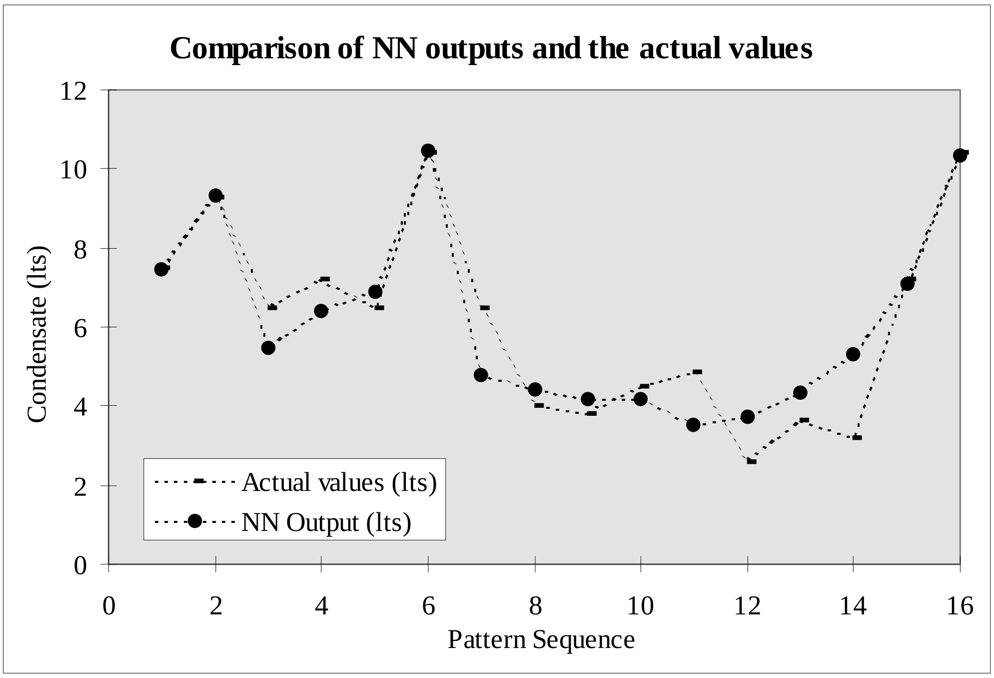


Figure 4: Result of NN Training.

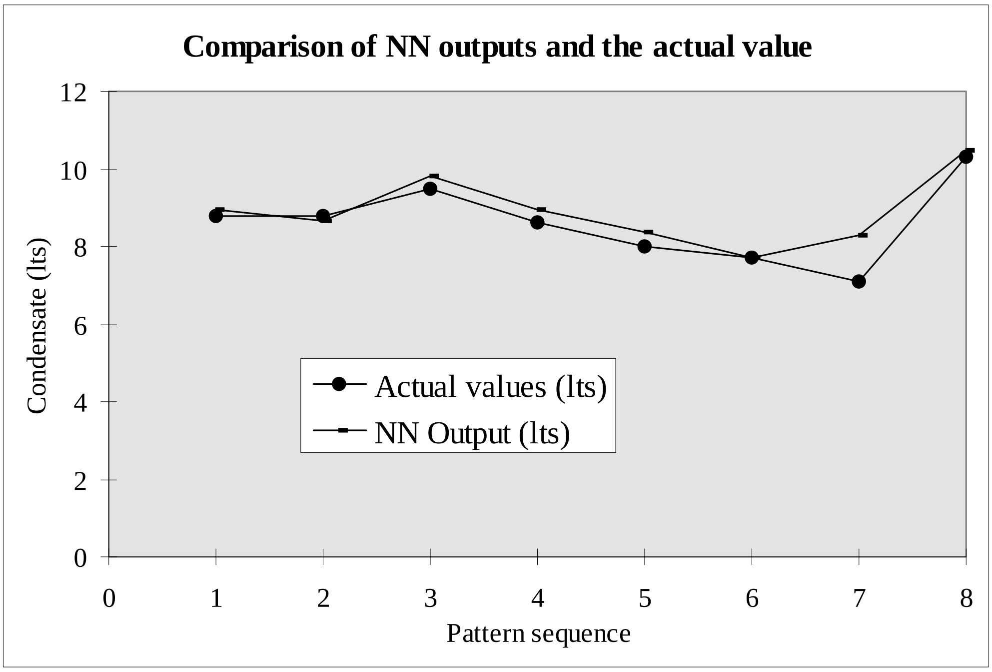


Figure 5: Result of NN Testing.