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A New Approach to Investigate the Energy Performance Of A Household Refrigerator-Freezer

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Abstract - *There are number of methods (i.e. engineering, regression) and computer tools (i.e. DOE-2, BLAST, HOT2000, ENERGY-10) for the modeling and forecasting of energy. Recently, a new approach artificial neural network has been widely used for load forecasting, solar energy, heating, ventilating, refrigeration, building energy analysis and so on in the field of energy as its (i.e. NN) prediction performance is better than other approaches in non-linear modeling analysis as has been found in literatures. A Neural Network (NN) also commonly referred to as an Artificial Neural Network, is an information-processing model inspired by the way the densely interconnected, parallel structure of the brain processes information. In this paper, experiments were conducted on a refrigerator to investigate the energy performance by varying the parameters (i.e. room temperature, door opening, internal cabinet temperatures, relative humidity and so on) that influence its energy consumption. Finally, experimental data were used to investigate refrigerators' energy prediction performance using NN approach. Statistical analyses in terms of fraction of variance* R^2, *Coefficient of variation (COV), RMS are calculated to judge the performance of NN model.*

Key words - **Refrigerator-freezers; Neural Networks, Energy, door opening, Statistical analysis**

1. INTRODUCTION

Malaysia, like other developing countries, has experienced dramatic growth in the use of household refrigerator-freezers. Economic growth is the main driving factor for higher use of refrigerator-freezers which, in turn, leads to the increasing need for comfort and a high style of living that has consequently caused a substantial increase in household energy consumption [1].

It has been found that refrigerator-freezer ownership level increased from 2,073,726 units in 1991 to 5,310,835 in 2004 in Malaysia [2]. This appliance is one of the major energy users in the household environment as it has to operate 24 hours in a day. A survey was conducted by [3] to investigate household energy patterns. Their study revealed that about 100% of total residential homes are equipped with one refrigerator-freezer. In some cases, they showed a multiple number of refrigerator-freezers owned by a single house owner. So, assessing (i.e. forecasting) its energy performance for policy implementation and efficiency improvement is very important.

Various forecasting techniques (i.e. time series, multiple linear regression, engineering, and econometric) have been proposed in the last few decades. Each of the techniques has its own advantages, disadvantages and limitations. Recently artificial neural networks have received tremendous attention for the prediction purpose in the field of energy and other field [4-9].

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The comparison of the results from NNs and statistical approaches indicated that neural networks offer an accurate alternative to classical methods such as multiple regression or autoregressive models. A more accurate prediction may be achieved with this method [10].

From the literatures it has been found that NN has been applied in the diverse field of energy, refrigeration properties, heat pump, engine performance, and so on. However, it has not been applied for the energy performance investigation of refrigerator-freezers. So the objective of this paper is to investigate the energy prediction performance of this appliance using NN approach using experimental data as input.

2. WORKING PRINCIPLE

NNs use simple processing units, called neurons, to combine data, and store relationships between independent and dependent variables. An NN consists of several layers with neurons that are connected to each other.

A widely used NN model called the multi-layer perceptron (MLP) NN is shown in figure 1. The MLP type NN consists of one input layer, one or more hidden layer (s) (middle) in between input and output layers and one output layer. Each layer employs several neurons (nodes), and each neuron in a layer is connected to the neurons in the adjacent layer with different weights. The weights, after training, contain meaningful information, whereas before training they are random and have no meaning [11].

Signals flow into the input layer, pass through the hidden layer(s), and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer. The incoming signals or input (x_{ij}) are multiplied by the weights (v_{ij}) and summed up with the bias ($_{bj}$) contribution. Mathematically it can be expressed as:

$$\text{net}_j = \sum_{i=1}^{n} X_i V_{ij} + b_j \quad (1)$$

an activation function to the total input and calculated using Equation 1 [12]. If the computed outputs do not match the known (*i.e.* target) values, NN model is in error. Then, a portion of this error is propagated backward through the network. This error is used to adjust the weight and bias of each neuron throughout the network so the next iteration error will be less for the same units. The procedure is applied continuously and repetitively for each set of inputs until there are no measurable errors, or the total error is smaller than a specified value.

Overtraining occurs when the net "memorizes the training pattern" instead of "learning from it". Overtraining (i.e. poor generalization) occurs when training phase is long or limited set of examples. One criterion to avoid overtraining is the early Stopping: the training is stopped when the error, computed on a limited data set, increases as shown in figure 2 [13-16].

3. APPLICATION OF NN IN THE PRESENT STUDY

In the present study, 6 input parameters (i.e. T_r, T_{ff}, T_{fz}, *L, RH, DO*) and one output parameter (i.e. energy consumption, *E*) were chosen. Each input layer consisting of 6 neurons and each output layer with one neuron were selected. One hidden layer with 6 neurons in between input and output were selected as this configuration gave best performance. Input and output layer and neurons are always fixed and number of hidden layer and its neuron is selected by trial and error method. SNNS 4.2 was used to train and test the network.

Network architecture with input, hidden, and output layers is shown in figure 3.

For ANNs, two data-sets are needed: one for training the network (approximately 80% of total data) and the second for testing (20% of total data) it.

Inputs and outputs have been normalized in the range of (0.1 to 0.9) as NN works efficiently within this range. Neurons in the input layer have no transfer function, while in the other layers a logistic sigmoid (logsig) transfer function has been used.

Scaling of numeric data (i.e. input) has been performed using the following equation [14]:

$$y_n = s_{\min}\left(\frac{y - y_{\min}}{y_{\max} - y_{\min}}\right)(s_{\max} - s_{\min}) \tag{2}$$

where,

s_{max} = is the maximum normalized data value equal to 0.9

s_{min} = is the minimum normalized data value equal to 0.1

y_n = value of the scaled input/output unit

y_{min} = minimum value of the input/output unit

y_{max} = maximum value of the input/output unit

3.1 Measure of Prediction Performance

Using the results produced by the network, statistical methods have been used to investigate the prediction performance of NN results. To judge the prediction performance of a network, several performance measures are used. This includes statistical analysis in terms of Root-Mean-Squared (RMS), absolute fraction of variance (R^2), Coefficient Of Variance (COV) as well as mean error percentage values has been calculated and defined as below [5-7], [11], [14-15]:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{\sum_{I=1}^{I=N} (E_a - E_M)^2} \right) \tag{3}$$

$$RMS = \sqrt{\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{N}} \tag{4}$$

$$CV = \frac{\sqrt{\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{N}}}{E_m} \times 100 \tag{5}$$

$$\text{Mean\% Error} = \frac{1}{\text{N}} \sum_{i=1}^{i=N} \left(\frac{E_a - E_p}{E_a} \times 100 \right) \tag{6}$$

Where

E_a - Actual result

E_p - Predicted result

E_m - Mean value

N - Number of pattern

The coefficient of multiple determinations R^2 compares the accuracy of the model to the accuracy of a trivial benchmark model. A perfect fit would result in an R^2 value of 1 and a very good fit near 1. The quality of fit decreases as the value of R^2 decreases.

4. EXPERIMENTAL SET-UP

4.1 Test Conditions

The objectives of this experiment were to determine the effect of room temperature, thermostat setting position (i.e. internal cabinet temperature), door opening, relative humidity, and loading on the energy consumption of household a refrigerator-freezer. The specification of the unit is shown in table 1. The tests were conducted by varying the room temperature, thermostat setting position or internal cabinet temperature, door opening, RH, and load independently. During the experiment, while one variable was changed, the other variables were kept constant.

The room temperature was varied from 16 ^{0}C to 32 ^{0}C in an environmentally controlled chamber located in our laboratory to investigate its effect on the energy consumption. The thermostat setting position was fixed at the medium setting (position 4 with internal fresh food and freezer temperature 4 ^{o}C and -13.3 ^{o}C respectively) and relative humidity was maintained at 60%. The refrigerator was loaded with a load of 7 kg water in the refrigerator-freezer and keeping the door 20 times open.

In a 24 hour period of operation time, the door was opened for the first 10 hours of the experiment. The door opening controls were set in such a way that the door remained open for 12 seconds at an angle of 90^o. In order to maintain 20 to 75 door openings over 10 hours of operation, door closing time was not fixed. Table 2 shows the door opening and closing schedule over these 10 hours. Room temperature and RH were maintained 24 ^{0}C and 60% respectively for all door opening tests and the thermostat setting position was kept at the medium position (position 4). The refrigerator was loaded with a load of 7 kg water in the refrigerator-freezer and keeping the door 20 times open.

Refrigerators' internal cabinet temperatures (i.e. fresh food and freezers' temperature) were varied by changing thermostat setting positions ranging from 1 to 7 for this test unit. Thermostat setting was varied by turning the knob to the desired setting position from 1 to 7 in order to investigate the effect of thermostat setting (i.e. internal cabinet temperatures as well) position on the energy consumption. Room temperature and RH were maintained at 24 ^{0}C and 60%, respectively. The refrigerator was loaded with a load of 7 kg water in the refrigerator-freezer and keeping the door 20 times open.

To investigate the effect of relative humidity on the energy consumption of the test unit, relative humidity was varied from 60% to 90%. The thermostat was set at position 4, room temperature was maintained at 24 ^{0}C, and refrigerator was loaded with a load of 7 kg water in the refrigerator-freezer and keeping the door 20 times open.

The effect of loading on energy consumption was investigated by placing fresh water into the unit. The load was varied from 7 kg to 18.0 kg in this test. The thermostat was set at position 4, room temperature was maintained at 24 ^{0}C, relative humidity was kept at 60%, and the refrigerator was loaded with a load of 7 kg water in the refrigerator-freezer and keeping the door 20 times open.

5. INSTRUMENTATION

A heat pump was used to maintain the required temperature in the environmentally controlled chamber in order to investigate the effect of room temperature. The various modes of operation of heat pump were (i) heating, (ii) cooling, and (iii) soft dry. The unit can maintain the controlled chamber temperature within 13 ^{0}C to 35 ^{0}C. The temperature fluctuations was controlled by using an Omega type temperature controller with an accuracy of ± 1 ^{0}C. The controller was interfaced with the heat pump so that the desired temperature could be maintained within the chamber. Daily energy consumption was measured by the YOKOGAWA WT-130 digital power meter, which was interfaced with a PC through RS-232. Lab view software was installed into the PC for data storage and analysis. The accuracy of this power meter is ± 0.2% of reading.

T-type thermocouples were used to measure the temperature inside as well as outside the test unit. An Omega HX-92 humidity transmitter was used to measure the relative humidity of the controlled chamber. Thermocouples and humidity transmitter were interfaced with a 20 channel HP data logger (Model 34970A) via a PC for data storage and analysis.

Relative humidity was varied from 60% to 90% by using a RECUSORB DR-010 dehumidifier with an accuracy of ±5% to investigate the effect of relative humidity on energy consumption. For the other tests, the relative humidity was maintained at 60±5%.

Instead of opening and closing the refrigerator-freezer manually, an automated door-opening and closing mechanism was designed and fabricated. A steel frame containing an AC motor and a gearbox were mounted on the top of the refrigerator-freezer. The door opening and closing arrangements are shown in figure 4. The door-opening process is controlled using the Programmable Logic Controller (PLC). The operating switch, which is an input device, sends signals to motor to open and close the door. Total run time, opening time, and closing time are inserted into the operating switch and it runs as per the experimental requirement.

6. PARAMETRIC STUDY OF REFRIGERATOR-FREEZERS ENERGY CONSUMPTION

The followings are the major factors that influence refrigerator-freezers' energy consumption: (i) ambient temperature, (ii) door openings, (iii) control/thermostat settings or compartment temperature, (iv) relative humidity, and (v) food loading.

6.1 Ambient Temperature

Most of the thermal load on a refrigerator-freezer is by conduction through the refrigerator-freezer wall. ASHRAE [17] shows that about 60% to 70% of the total refrigerator-freezer load comes through conduction of the cabinet walls. This conduction load is proportional to the difference between ambient temperature and internal compartment/freezer temperature. The higher the difference, the higher the load imposed on a refrigerator-freezer. For this reason, the temperature of the air around a refrigerator-freezer is a significant determinant of energy consumption. Since compressor efficiency also declines as the ambient temperature rises, a refrigerator-freezer's electricity use is very sensitive to the ambient temperature. Meier [18] stated that energy consumption varies from1.25 kWh/day to 2.6

kWh/day for an 11 ^{0}C increase in temperature. Author conducted the experiment for a US style refrigerator.

In this experiment, energy consumption increased 560 Wh/day to 1120 Wh/day when the temperature increased from 16 ^{0}C to 31 ^{0}C in a Malaysian produced model. Energy consumption increased around 40 Wh for a 1 ^{0}C increase in temperature.

6.2 Door Openings

When the refrigerator-freezer door is opened, warm and moist air mixes with the cool air inside the refrigerator-freezer cabinet. When the door is closed, a mass of air at ambient temperature is trapped into the compartment. Heat gain during door openings are due to (i) heat/vapor transfer on the interior surfaces of refrigerator-freezer, and (ii) bulk air exchange.

The following five categories of loads are associated with the door openings Alissi (1987). These are:

(i) convective heat transfer from the warm ambient air flowing across the cooler refrigerator surfaces;
(ii) latent heat transfer with condensation of water vapor from the moist air flowing across the cooler refrigerator surfaces;
(iii) radiative heat transfer from surroundings to the interior surfaces;
(iv) sensible heat transfer from the warm air mass within the cooled space after door is closed; and
(v) latent heat transfer due to dehumidification of the air after door is closed.

Alissi [19] showed about a 32% increase in refrigerator-freezer energy consumption for 100 door openings. Grimes et al. [20] found a 6 to 8% higher energy consumption for 24 door openings. Parker and Stedman [21] estimated that each door opening causes 9 Wh of increased energy consumption. This experiment has been carried out with multiple door inopenings, beginning with 20 and reaching 75 during the first 10 hours of commencement of operation.

This investigations show about a 10 Wh increase in energy consumption for each door opening.

6.3 Effect of Thermostat Setting or Internal Temperature

A refrigerator-freezer will consume less electricity if its thermostat is re-set to a higher (warmer) temperature. Owing to the single-evaporator design of most refrigerator-freezers, a change of temperature in the freezer compartment generally results in a temperature change in fresh-food compartment. Grimes et al. [20] examined the impact of compartment temperature on energy use on a 1977-vintage automatic defrost refrigerator. Energy consumption rose 26% from the warmest acceptable to the coldest possible settings. A more recent study of nine large, 1993-vintage US refrigerator-freezers Meier [22] found a 6.5% increase energy consumption for a 1 ^{0}C reduction in freezer temperature.

We have conducted experiments from warmest thermostat setting (position 1) to coldest thermostat setting (position 7) to investigate its effect on the energy consumption. In this investigation average, warmest, medium, and coldest thermostat setting temperatures were around –4 ^{0}C (setting position 1), -13.3 ^{0}C (setting position 4), and –18 ^{0}C (setting position 7), respectively. Energy consumption increased about 790 Wh from warmest to coldest position. This is about a 10% increase in energy consumption for each degree decrease in temperature.

6.4 Effect of Relative Humidity

Humidity has little effect on energy consumption. Grimes *et al.* [20] reported a 5% increase energy consumption when the relative humidity was increased from 40% to 60%. The greatest energy impact of humidity is probably the operation of the electric resistance anti-condensation heaters. When humidity increases, vapor condenses at the wall of refrigerator-freezer. An anti-sweat heater turns on to prevent condensation raising refrigerator-freezer energy consumption. In this experiment, we raised the humidity from 60% to 90% and the corresponding energy consumption increase was 10%.

6.5 Effect of Loading on Energy Consumption

One study [23] reported that the heat removed from food loadings accounted for the majority of the refrigeration load. This load is the function of product type, mass, and temperature difference before and after cooling of the product. However, one survey in [24] concluded that loading has very little effect on energy consumption, although the authors could not find a general conclusion. The primary sources of refrigeration load from products brought into and kept in the refrigerated spaces are (i) heat removal required to reduce the product temperature from receiving to storage temperature, and (ii) heat generated by products in storage, mainly fruits and vegetables. The quantity of heat to be removed can be calculated from knowledge of the product, including its state upon entering the refrigerating space, final state, mass, specific heat above and below freezing temperature, and latent heat. When cooling a definite mass of product from one state and temperature to another, the following loads are associated in accordance with Ref. ASHRAE [25]:

(1) Heat removal in cooling from the initial temperature to some lower temperature above freezing:

$$Q = mc_1(t_1 - t_2) \tag{7}$$

(2) Heat removal in cooling from the initial temperature to the freezing point of product:

$$Q_2 = mc_1(t_1 - t_f) \tag{8}$$

(3) Heat removal to freeze the product:

$$Q_3 = mh_{if} \tag{9}$$

(4) Heat removal in cooling from the freezing point to the final temperature bellow the freezing point:

$$Q_4 = mc_2(t_f - t_3) \tag{10}$$

Refrigeration system capacity for products brought into refrigerated spaces is determined from the time allotted for heat removal and assumes that the product is exposed in a manner to remove the heat in that time. The calculation is:

$$q = \frac{Q_1 + Q_2 + Q_3 + Q_4}{3600n} \quad (11)$$

Latent heat of fusion of a product is related to its water content and can be estimated by multiplying the percent of water in product by the latent heat of fusion of water.

The experiment was conducted by placing fresh water of 24 ^{0}C to 25 ^{0}C into the fresh food and freezer compartments. Tests were performed with water loaded in both compartments. It has been found that energy consumption increases by about 90 Wh per kg of water. Energy consumption increases by 78% from minimum load to maximum load.

Although there is a significant increase in energy consumption due to the increase in load, other factors must be taken into consideration. In actual kitchen conditions, a household refrigerator-freezer is usually equipped with vegetables, meat, fruits, and so on, which differently influence the energy consumption. Energy expended in removing heat from those products has been explained in Eqs. (7) through (11). Once the product attains the desired cooling temperature, it does not effect the energy consumption significantly until fresh products are placed in again. If the products remain for several days in the refrigerator-freezer after cooling to desired temperature, an increase in the energy consumption may be attributed to the loading of fresh food during that period. So, a general conclusion would not be possible.

7. PREDICTION RESULTS USING ANN

The statistical values such as RMS, R^2, COV and MPE are given in table 3. The values in the table are for the most suitable algorithms and for the hidden layer giving the most appropriate approach. However, no results for other hidden neurons were given in this paper.

Figure 5 shows the typical comparative plots between measured and neural network predicted output. From the figure, it has been observed that the predicted energy consumption is very close to the actual values with a small perceptible deviation. This result shows close agreement between the NN predictions and the actual values.

Table 3 shows that R^2 for this network is 0.979723 for training set and 0.968763 for testing set, which is a proof of a very good fit. From the table 3 it has been observed that mean percentage error for training and testing are 0.001854939 and 0.002375693 respectively. This means error is negligible.

8. FIGURES AND TABLES

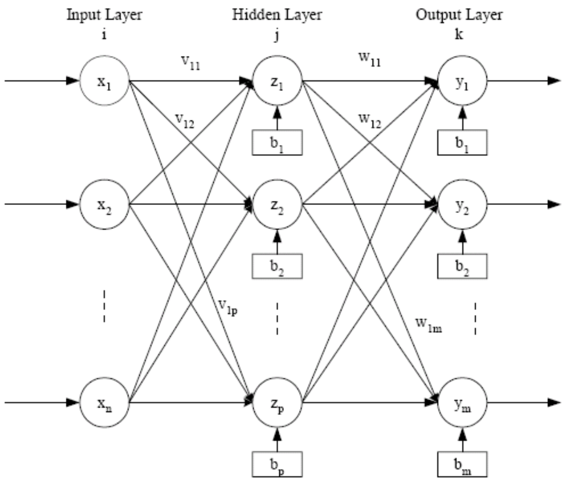

Fig. 1. Architectural graph of an MLP with one hidden layer (Kalogirou, 2000).

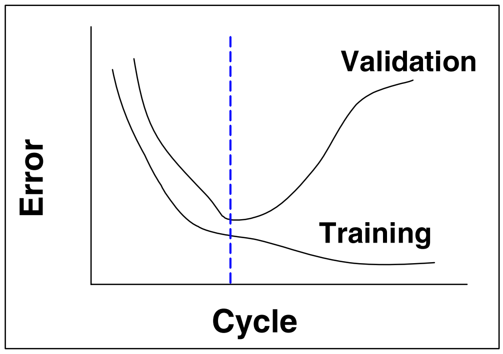

Fig. 2. Variation of error at different cycles for training and validation data set.

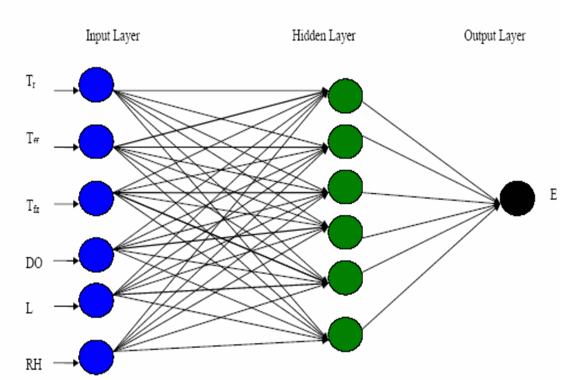

Fig. 3. Network architecture with input, hidden, and output layers.

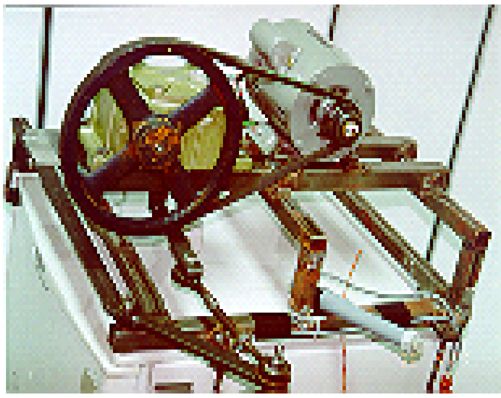

Fig. 4. Door opening and closing arrangements.

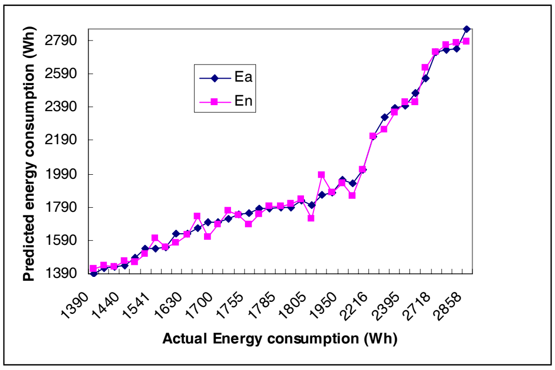

Fig. 5. Actual vs neural network predicted energy consumption.

Table 1. Technical Specifications of the Test Unit

Specifications	*Values*
Freezer capacity	40 L
Fresh food compartment capacity	110 L
Power rating	115 W
Current rating	0.67 A
Voltage	240 V
Frequency	50 Hz
No of door	1
Refrigerant type	134a (CF_3CH_2F)
Defrost system	Partial auto

Table 2. Door Opening Schedule

No of opening	Total run time (minute)	Closing time (minute)	Door remains open (sec)
20	600	30	12
30	600	20	12
40	600	15	12
50	600	12	12
60	600	10	12
75	600	8	12

Table 3. Measures Used to Judge the Performance of NNs

	R^2	*CV*	*RMS*	*Mean % Error*
Training	0.979723	0.874964	0.016378	0.001854939
Testing	0.968763	0.882945	0.019564	0.002375693

9. CONCLUSIONS

Following conclusion can be made from this study:

It can be stated that the predicting ability of the ANN model is very good as R^2 value is close to 1 and MBE is very small. The results showed that the ANN approach could be considered as an alternative and practical technique to evaluate the energy performance of refrigerator-freezers compared to experimental investigations. It is feasible due to its ability to learn and generalize the complex data set with a wide range of experimental conditions.

10. NOMENCLATURE

- *DO* : Door opening
- *E* : Energy
- E_a : Actual Energy consumption
- E_n : Neural Network predicted energy consumption
- *L* : Load (kg)
- *RH* : Relative Humidity (%)
- T_{fz} : Freezer compartment temperature (^{0}C)
- T_{ff} : Fresh food compartment temperature (^{0}C)
- T_r : Room temperature (^{0}C)
- c_1 : Specific heat of product above freezing point (kj/kg.K)
- c_2 : Specific heat of product below freezing point (kj/kg.K)
- h_{if} : Latent heat of fusion of the product below freezing point (kj/kg.K)
- *m* : Mass of the products (kg)
- *n* : Allotted time period (hour)
- Q_1, Q_2, Q_3 and Q_4 Heat removal (kj)
- *Q* : Product cooling load (kW)
- t_1 : Initial temperature of product above freezing point (^{0}C)
- t_2 : Lower temperature of product above freezing point (^{0}C)
- t_3 : Final temperature of product below freezing point (^{0}C)
- t_f : Freezing temperature of product (^{0}C)

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