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Modelling of a locally fabricated flat-plate solar milk pasteuriser using artificial neural network

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The objective of this work was to develop an artificial neural network model to predict milk temperature of a locally fabricated solar milk pasteuriser, based on measures of error deviation from experimental data. A three-layer feed-forward neural network model based on back propagation algorithm was developed using the Neural Network Toolbox for MATLAB®. The inputs of the model were ambient air temperature, solar radiation, wind speed, temperature of hot water, and water flow rate through the collector, whereas the output was temperature of milk being pasteurised. The optimal neural network model had a 4-4-1 structure with sigmoid transfer function. The neural network predictions agreed well with experimental values with mean squared error, mean relative error and correlation coefficient of determination (R^2) of 5.22°C, 3.71% and 0.89, respectively. These results indicate that artificial neural network can successfully be used for the prediction of the performance of a locally fabricated solar milk pasteuriser.

Key words: Artificial neural network, modelling, solar milk pasteuriser.

INTRODUCTION

Milk marketing is an important income earning opportunity for people in the arid and semi-arid lands (ASALs) of Kenya. To minimise losses along the marketing chain, traders boil milk using firewood, especially when transport to the market is unavailable. This, however, places intense pressure on woody resources on the already fragile environment (McPeak, 2003). Therefore, alternative cheap and renewable energy technologies such as solar energy should be provided to small scale farmers and traders who are involved in milk marketing. Kenya has enormous amounts of solar energy resource particularly in the ASALs, where the monthly average of global solar radiation varies from 13.3 to 30.6 $MJ.m^{-2}$ day^{-1} (Kenya Meteorological Department, Solar radiation records 2000-2009, unpublished) and, therefore, solar milk pasteurisers seem to be viable alternatives to firewood for heating milk.

Solar milk pasteurisers should be optimally designed and operated, and prediction of temperature of milk being pasteurised is one of the important parameters to be accurately determined. Prediction of pasteurisation temperature helps to know the potential temperatures attainable by the device and to ensure adequacy of pasteurisation, that is, correct pasteurisation temperatures (63°C for 30 min) are achieved. Classical modelling techniques are complex and require long computing time for their solution, and are sometimes totally unrealisable (Khadir, 2005; Tripathy and Kumar, 2008). As an alternative to classical modelling techniques, thermal solar energy systems can accurately be modeled using Artificial

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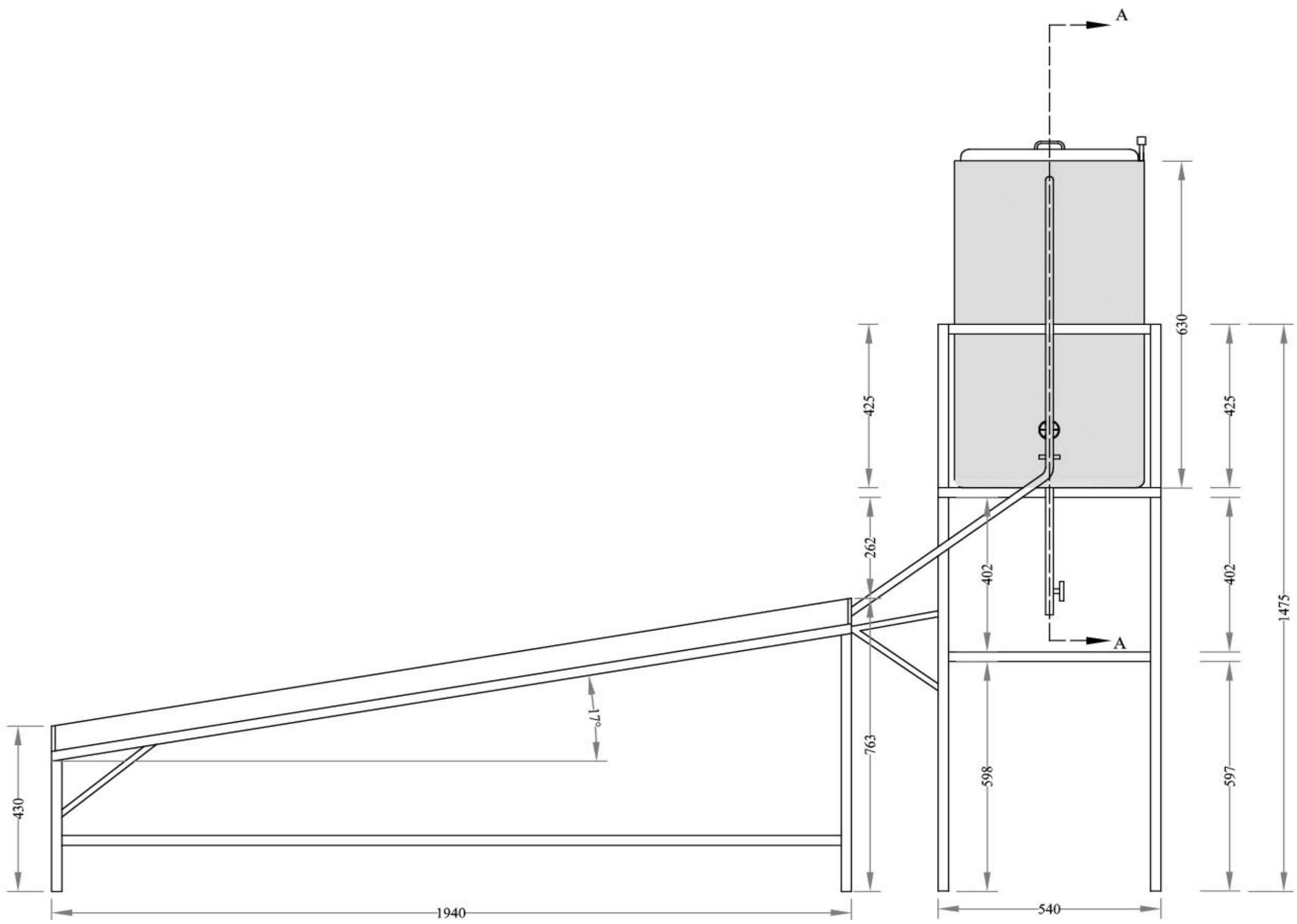

Figure 1. Side view of the solar milk pasteuriser (All figures in mm).

Neural Networks (ANN) (Kalogirou et al., 1999). Artificial neural networks are mathematical models which have the capability of relating the input and output parameters, learning from examples through iteration, without requiring a prior knowledge of the relationships between the process parameters, thus easily modelling physical phenomena in complex systems under given conditions with reasonable accuracy (Basheer and Hajmeer, 2000; Fadare, 2009). Interest in using ANNs as a modelling tool in food technology has been increasing in the recent past, with results demonstrating the superiority of ANNs over classical modelling techniques (Huang et al., 2007). Artificial neural networks have been used to predict temperature during high-pressure food processing (Torrecilla et al., 2005), microwave drying of tomato slices (Poonnoy et al., 2007) and industrial food processes (Khadir, 2005). However, data on modelling of low cost flat-plate solar milk pasteurisers in Kenya using ANNs is not available. The present study was, therefore, planned to develop and validate an ANN model to predict milk temperature of a locally fabricated solar milk pasteuriser, based on measures of error deviation from experimental data. The developed network could then be used as a design tool for estimating the performance of solar milk pasteurisers. Requiring only a limited number of tests, this new approach can reduce time and engineering effort spent for numerical studies or comprehensive experiments, thus helping the manufacturer.

MATERIALS AND METHODS

Flat plate solar milk pasteuriser and data collection

The ANN modelling was applied to a locally fabricated solar milk pasteuriser made up of a flat plate water heating solar collector and a jacketed milk pasteurisation vat (Figures 1 and 2). Milk was pasteurised by hot water produced by the solar collector. The equation of the collector efficiency (η) was:

$$\eta\ (\%) = 75.8 - 833.2\ (T_i - T_a)/I \quad (1)$$

where (T_i) is the inlet water temperature in the solar collector (°C), T_a is the ambient temperature (°C) and I is the insolation in plane of solar collector (W.m^{-2}).

The solar collector was tilted at 17° from the horizontal, facing the equator. The collector absorbs solar radiation, transforms it into heat energy and conducts the heat into water flowing through the

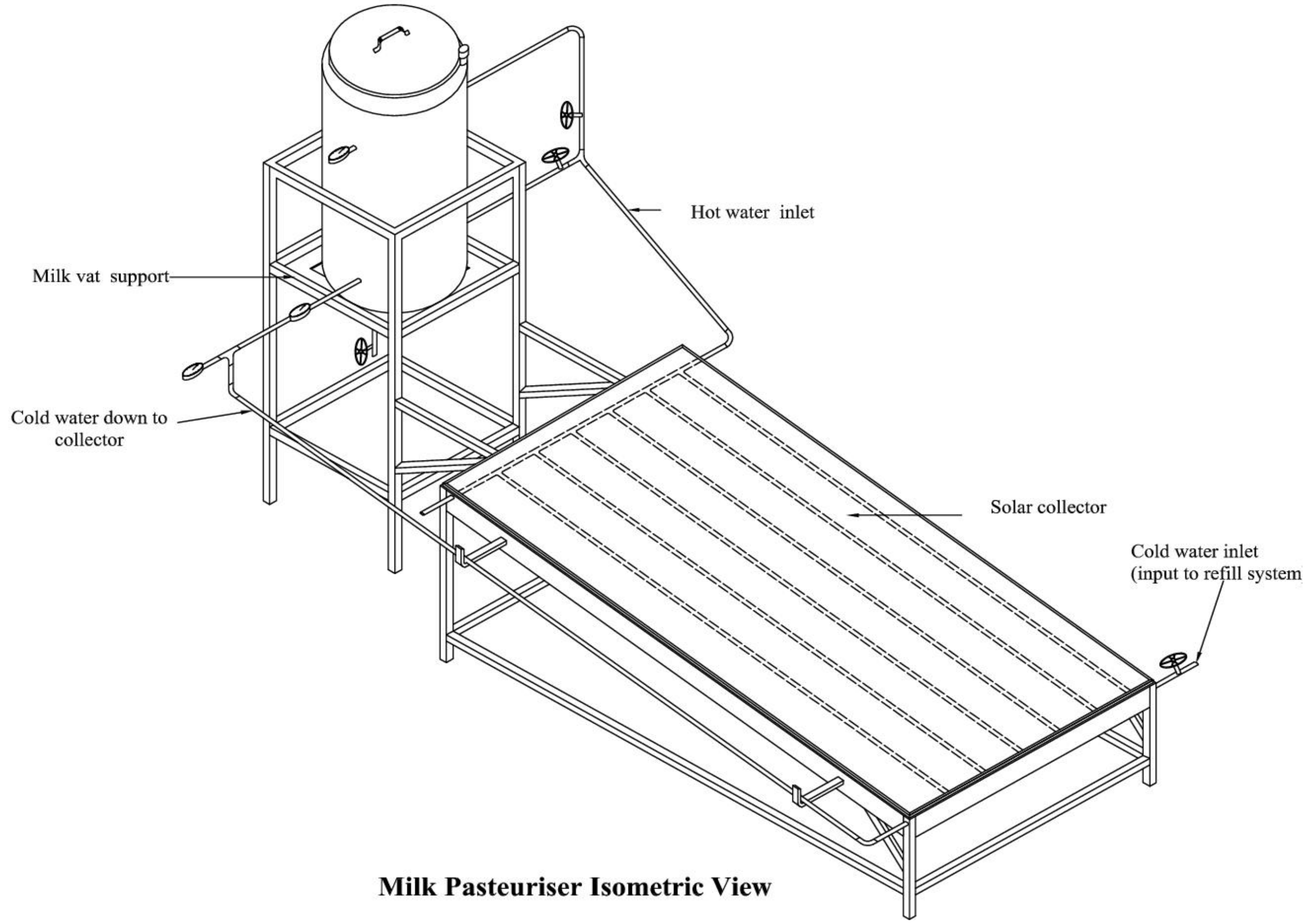

Figure 2. Isometric view of the solar milk pasteuriser showing the solar collector and milk container.

collector pipes. One pipe from the collector circulates hot water from the collector to the top of the milk vat. Another pipe from the bottom of the milk vat circulates cooler water in to the collector. These pipes were properly insulated with cotton wool to minimise heat losses.

The system was tested in July to August 2010 at the Kenya Agricultural Research Institute (KARI), National Arid Lands Research Centre, Marsabit (37.97°E, 2.32°N, altitude 1219 m), where the average solar radiation and ambient temperature ranged from 10.9 to 28.5 $MJ.m^{-2}.day^{-1}$ and 23 to 38°C, respectively. Parameters measured included temperature of milk, T_m (°C), temperature of hot water, T_w (°C), water flow rate through the collector, $\dot{m}$ ($kg.s^{-1}$), ambient air temperature, T_a (°C), solar radiation, I ($W.m^{-2}$) and wind speed, v ($m.s^{-1}$). These measurements were recorded approximately every hour. Milk and water temperature were measured using digital K-Type thermocouple thermometer (type HI 9043, Hanna Instruments, Padova, Italy). Water flow rate through the collector was measured by a rotameter (G. A. Platon Ltd., Basingstoke, U.K., measuring range: 0.76 to 5.7 $L.min^{-1}$). Ambient temperature was measured by digital thermometer (0 to 60°C, Model No. ETH529, Brannan Thermometers, Cleator Moor, Cumbria, England). Solar radiation data were measured by pyranometer (Kipp and Zonen, Delft, Netherlands) and wind speed by cup-and-vane anemometer, which indicated wind speed values in the range of 0 to 30 $m.s^{-1}$ (full scale = 10 divisions; 1 division = 3 $m.s^{-1}$). A total of 216 data sets on each variable were collected.

Modelling with artificial neural network

The architecture of the ANN for the solar milk pasteuriser with the names of input and output parameters is schematically illustrated in Figure 3. This architecture has been used for modelling solar energy systems with very good results (Kalogirou et al., 1999), and is the most popular and versatile type of networks in food applications (Huang et al., 2007). The input layer has five neurons corresponding to the five input parameters: T_a, I, v, T_w and $\dot{m}$. The output layer consists of one neuron, representing the dependent variable T_m, which the network produces for the corresponding inputs. The logistic sigmoid transfer function (Equation 1) was used in the hidden and output layers. This is the most commonly used transfer function in back propagation algorithm (Basheer and Hajmeer, 2000).

$$f(x_j) = \frac{1}{1+e^{-x_j}} \qquad (1)$$

where x_j is the weighted sum of the input (the net effect). The logistic sigmoid function possesses the distinctive properties of

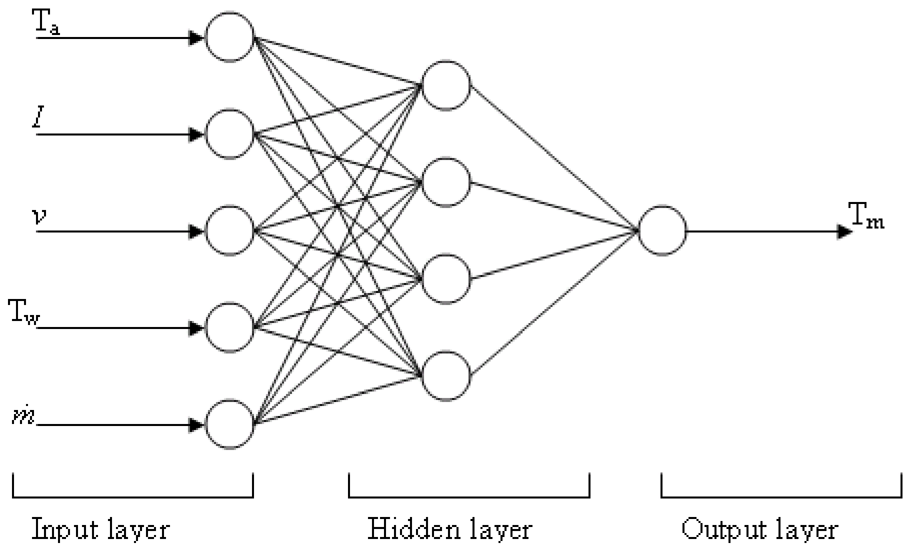

Figure 3. Structure of the ANN for the analysis of solar milk pasteuriser. T_a, Ambient air dry bulb temperature (°C); *I,* solar radiation (W.m^{-2}); *v,* wind speed, (m.s^{-1}); T_w, temperature of hot water (°C); $\dot{m}$, water flow rate through the collector (kg.s^{-1}); T_m, temperature of milk (°C).

Table 1. Sample of input and output parameters used for training the network on a test day.

Standard local time (h)	Inputs					Output
	Ambient air temp*, T_a (°C)	Insolation, I (W.m^{-2})	Wind speed, v (m.s^{-1})	Temp of water jacket, T_w (°C)	Water flow rate, $\dot{m}$ (kg.s^{-})	Temp. of heated milk, T_m (°C)
10.00	25.1	986.1	5.4	24.5	0.0124	24.5
11.00	24.1	870.4	5.9	26.7	0.0107	24.7
12.00	27.1	719.9	6.6	30.7	0.0175	29.7
13.00	26.5	1018.5	8.7	66.0	0.0225	64.3
14.00	25.7	932.9	8.7	66.0	0.0227	64.2
15.00	25.7	828.7	9.3	65.1	0.0225	64.1
16.00	24.4	956.0	5.4	63.2	0.0334	63.5
17.00	23.4	932.9	5.5	64.2	0.0450	63.2

Temp*, Temperature.

continuity and differentiability on (–∞, ∞), essential requirements in back propagation learning (Basheer and Hajmeer, 2000; Huang et al., 2007). Information processing at each node was performed by combining all input numerical information from upstream nodes in a weighted average of the form given in Equation 2:

$$x_j = \sum_{n=1}^{n} w_{ij}.y_i + b_n \quad (2)$$

where $w_{ij}.y_i$ is the multiplication of the input variables (y_i) with their corresponding connection weights (w_{ij}) at location *n* and b_n is a constant term referred to as the bias associated with neuron *n* (that is, the neuron's threshold limit). The subscript $_j$ refers to a summation of all neurons in the previous layer and $_i$ to the neuron position in the present layer. In the same way, the prediction values (y_k) were calculated taking as inputs the corresponding output values of the previous hidden layer neurons (y_j) and multiplying them by the connection weights w_{jk}.

Training, validation and testing of the network

The available data set, which consisted of 216 input vectors and their corresponding output vectors from the experimental work, was divided randomly into training (75%) and testing/validation (25%) subsets. A sample of the data used for training the network is shown in Table 1. Kalogirou et al. (1999) used 54 data points and developed an ANN model which successfully predicted the performance of a thermosiphon solar water heater.

Training was done in batch mode using back-propagation Levenberg-Marquardt optimisation algorithm. This is a supervised training rule with multiple-layer networks, in which the network weights are moved along the negative gradient of the mean squared error (MSE) so as to minimise the difference between the network's output (y_k) and the desired target (r_k), that is, experimentally measured value (Basheer and Hajmeer, 2000). At the beginning of the training phase, the weights and biases of the ANN were randomly initialised between 0 and 1; the choice of small numbers being very essential to reduce the likelihood of premature neurons saturation leading to slow or no learning (Basheer and Hajmeer, 2000).

For the given set of inputs to the network, y_k was calculated and compared with r_k. Then the prediction error associated with the output response (E_k) was computed according to Equation 3:

$$E_k = \frac{1}{2}\sum_k (r_k - y_k)^2 \quad (3)$$

The weights were adjusted to reduce the prediction errors through a back-propagation algorithm where E_k was back-distributed to the previous layers across the network. The optimisation of the connection weights was performed minimising the error according to Equation 4:

$$w_{jk} = w^0_{jk} - \mu . \frac{\partial E_k}{\partial w_{jk}} \quad (4)$$

where w^0_{jk} is the initial connection weight and μ the learning coefficient. This coefficient controls the degree at which the connection weights are modified during the training phase.

Solving Equation (4) leads to:

$$w_{jk} = w^0_{jk} - \mu . (r_k - y_k) . y_k . (1 - y_k) \quad (5)$$

for connection weights corresponding to the output layer or to:

$$w_{jk} = w^0_{jk} - \mu . \sum_k (r_k - y_k).y_k.(1 - y_k).w_{jk}.y_j .(1-y_j).y_i \quad (6)$$

for connection weights corresponding to the hidden layer.

After the weights were modified, the next data set was fed to the network, and a new estimation was made. The error was calculated again and back-distributed across the network for the next modification. The neuron number in the hidden layer was tested between 2 and 10, and prediction error associated with the output response calculated for each of them. The whole process was repeated over 4930 iterations, while the prediction error decreased and training ended as soon as the error began to rise. At this moment, the weights were assumed as optimised and the optimal number of neurons in the hidden layer was selected as 4. The network training was frozen and a set of completely unknown test data was applied for testing.

In the testing step the competence of the trained network was evaluated. Fifty six (56) independent test data sets, never shown before, were presented to the ANN. At this point, no corrections of the connection weights were made and the ANN was only used to predict T_m. The computer code for training and testing the ANN was implemented under MATLAB® environment (version 7.8, MathWorks Inc., Natick, MA, USA), using the Neural Network Toolbox (Demuth et al., 2009).

Statistical analysis

Statistical measures namely, MSE, mean relative error (MRE) and correlation coefficient of determination (R^2) (Equations 7 to 9) were computed to check the performance of the developed model against the experimentally obtained values.

$$\text{MSE} = \frac{1}{n} . \sum_{i=1}^{n} (y_k - r_k)^2 \quad (7)$$

$$\text{MRE (\%)} = 100 . \frac{1}{n} . \sum_{n=1}^{n} \frac{|y_k - r_k|}{r_k} \quad (8)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (y_k - r_k)^2}{\sum_{i=1}^{n} (y_k)^2} \right) \quad (9)$$

where n is the number of data points. The optimum ANN configuration which gave the lowest MSE and MRE and highest R^2-value for the training dataset was selected. t-test was also carried out in SPSS Statistics Version 17.0 (SPSS, 2008) to determine if there were significant differences between real experimental data and those predicted by the ANN.

RESULTS AND DISCUSSION

Optimum network configuration

Error measures associated with different ANN configurations for prediction of milk temperature with different data sets are presented in Table 2. The network model with four neurons in the hidden layer resulted in the best prediction. The MSE, MRE and R^2 for this configuration were 2.11, 4.94%, and 0.99, respectively (bolded in Table 2). Thus, the ANN model with one hidden layer and four neurons in the hidden layer was selected as the optimum network for validation using a smaller data set consisting of 56 cases, giving a network with the structure 4-4-1.

Training and validation

A plot of the variation of training, validation, and test errors with the number of training epochs is shown in Figure 4. The graph shows MSE of the network starting at a large value and decreasing to a smaller value, that is, the network is learning. The error in the training set decreases as the weights are improved. Training stopped when the validation error begun to increase after 12 epochs. The result is reasonable because the final MSE is small, the test and validation set errors have similar characteristics, and no significant over-fitting had occurred by epoch 12 (where the best validation performance occurred). The training data were learned with an excellent accuracy; the MSE, MRE and R^2 were 2.11, 4.94%, and 0.99, respectively. Mapping between input and output data was performed at a satisfactory level since MSE and MRE are very small (close to zero) and R^2 value close to unity. These results imply that the designed ANN model is stable and reliable, and can be used to predict milk temperature of the solar milk pasteuriser.

Regression analysis with training, validation, test and all data is shown in Figure 5. The dashed line is the perfect line where outputs and targets are equal. The

Table 2. Network performance errors with various neurons in the hidden layer during training.

No. of neurons in the hidden layer	Mean squared error (MSE)	Mean relative error (MRE) (%)	R^2
2	2.81	6.33	0.99
3	2.71	6.32	0.99
4	**2.11**	**4.94**	**0.99**
5	4.20	5.06	0.99
6	4.30	6.17	0.99
7	3.12	6.18	0.99
8	2.75	8.13	0.99
9	4.61	7.16	0.98
10	4.49	6.92	0.97

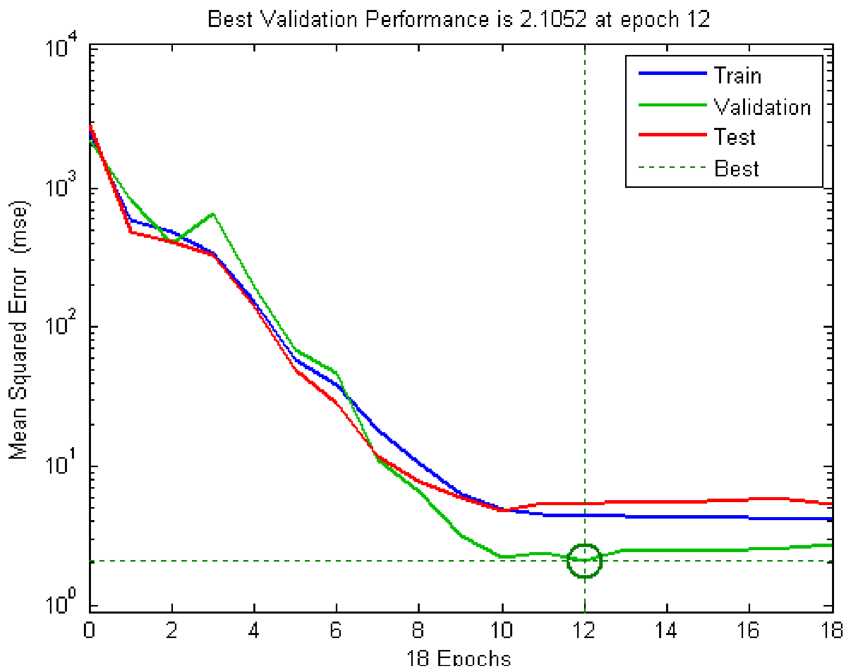

Figure 4. Evolution of training, validation and test errors as a function of the number of learning epochs during ANN training.

circles are the data points and coloured line represents the best fit between outputs and targets. The circles gather across the dashed line, meaning the outputs are not far from the targets. According to these results, it can be concluded that the ANN structure is satisfactory to predict the temperature of milk during solar pasteurisation. Variation of gradient error, μ and the validation error is shown in Figure 6. The figure also shows that the training process was stopped when the gradient error reached a minimum value at epoch 18.

Testing

Comparison between the ANN-predicted and experimental milk temperature is shown in Figure 7. The comparison was made using data only from the test set, which was not introduced to the ANN during the training. The ANN predictions for the milk temperature with respect to the experimental values resulted in a MSE, MRE and R^2 values of 5.22°C, 3.71%, and 0.89, respectively. The maximum and minimum deviation between actual and predicted values for milk temperature was 5.3 and 0.1°C, respectively. These values are considered adequately accurate for design purposes. The magnitude of errors reported here was generally in the same order as found earlier by Kalogirou et al. (1999) during modelling of a solar water heater. The ANN model presented here is another simulation approach which can be used to predict very quickly the performance of a locally fabricated

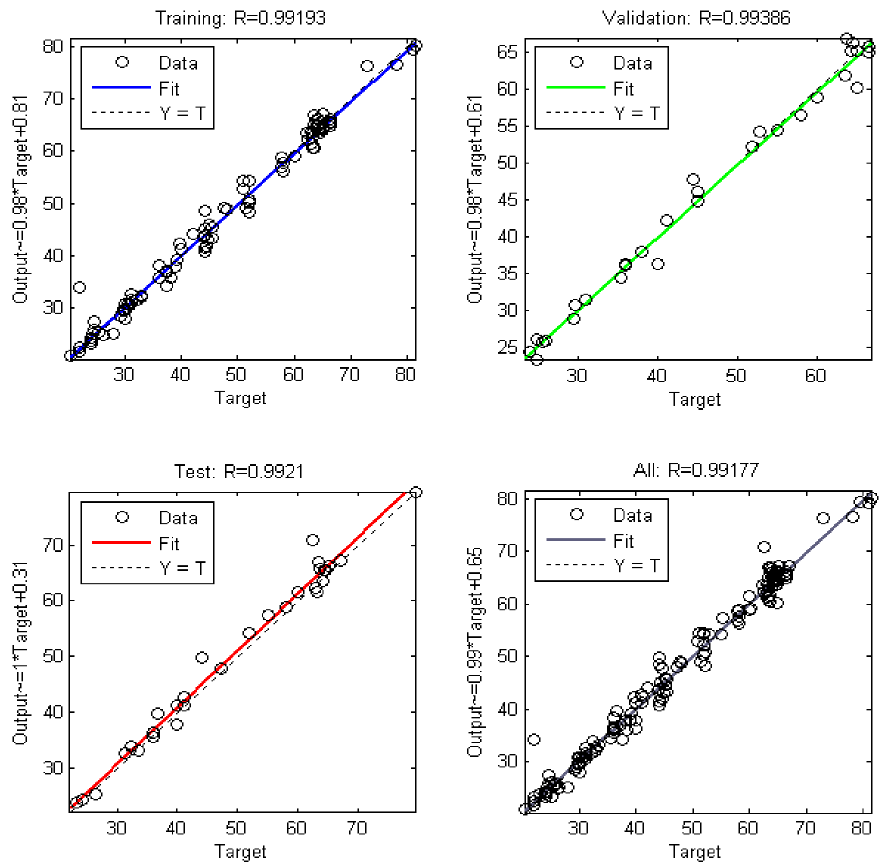

Figure 5. Regression analysis with training, validation, test and all data for the optimum ANN.

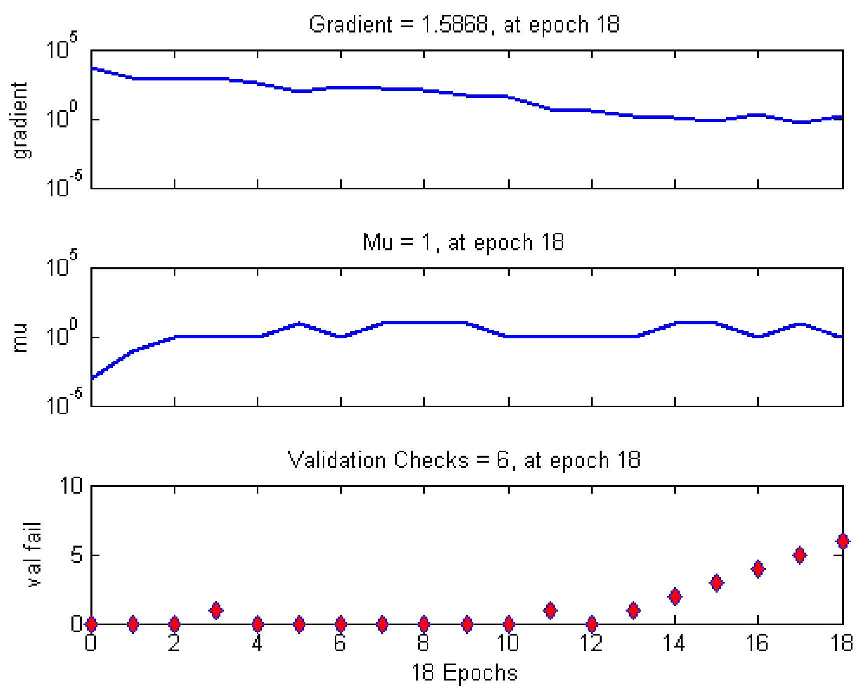

Figure 6. Variation of gradient error, μ and the validation error. Val, validation error; mu, μ (learning coefficient); gradient, gradient error.

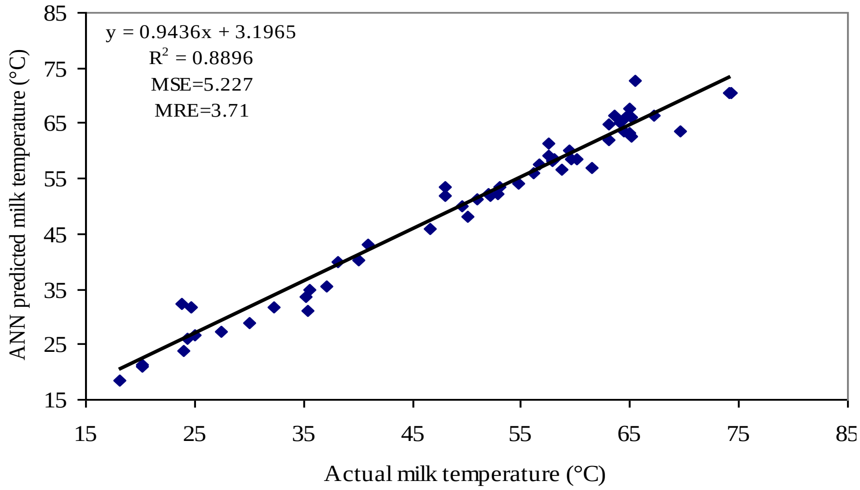

Figure 7. Comparison of experimentally measured and ANN-predicted values for milk temperature using the optimal network with the testing dataset, p=0.80 (n=56).

solar milk pasteuriser. Real (experimentally determined) and ANN predicted milk temperature were not significantly different (t-test, p=0.80), which corroborates the finding of Torrecilla et al. (2005) who found no significant difference between experimental and ANN predicted values during high-pressure food processing. The finding in this study show that ANN provides a tool that can be used to avoid the shortcomings involved in comprehensive experiments during fabrication of solar milk pasteurisers. The solar milk pasteuriser was tested in Marsabit (37.97°E, 2.32°N, altitude 1219 m), but the model could give good predictions for systems located anywhere in the ASALs of Kenya since flat-plate collectors are not sensitive to the geographic latitude (Kalogirou et al., 1999) and ANNs are able to generalise (Basheer and Hajmeer, 2000). Other advantages of ANNs include faster speed of information processing, learning ability and fault tolerance (Basheer and Hajmeer, 2000; Huang et al., 2007). It can, therefore, be concluded that by performing a small number of experiments and by using the data to train a suitable network, one can produce a model of the system, which can be used to predict the performance of the system under any weather conditions.

CONCLUSIONS AND RECOMMENDATIONS

The applicability of the ANN approach for modelling the performance of a locally fabricated solar milk pasteuriser has been studied. Employing data acquired from experiments, a three-layer feed-forward ANN model based on back propagation algorithm was developed, and used to predict the temperature of milk being pasteurised. The model resulted in good statistical performance between experimental and predicted values, with MSE, MRE and R^2 of 5.22°C, 3.71% and 0.89, respectively. Predictions with maximum deviations of5.3°C (11.1%) were obtained, which is within the acceptable accuracy level used by design engineers. The study reveals that ANN can be used as a design tool to predict the performance of locally fabricated flat-plate solar milk pasteurisers, and adds value to the optimisation process by reducing time and engineering effort spent in exhaustive experimentations (that is, design, construction and testing of prototypes), and the uncertainties in tedious computational routines of complicated mathematical models. To improve generalisation ability of the model, the technique of cross validation should be used in future work.

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