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ORIGINAL RESEARCH

Prediction of the performance of an on-farm direct expansion bulk milk cooler using artificial neural networks

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The performance of an on-farm direct expansion bulk milk cooler (DXBMC) is predicted through the use of artificial neural network models. Data was collected at an existing farm for the period of April 2016–March 2017. The data were submitted to MATLAB to develop artificial neural networks (ANNs) and simulate the energy consumption and coefficient of performance (COP) of the DXBMC. The data was split 70:15:15, representing training, validation and testing datasets respectively. Two ANNs were developed for the energy consumption and COP respectively. Several neural networks were created and trained in a systematic procedure. Selection of the best combination of predictors for the models was based on the coefficient of determination (R), root mean square error (RMSE) and mean absolute percentage error (MAPE). The importance of the inputs to the output were also deduced. The results showed high precision in predictions for both energy consumption and COP, as the values of the MAPE were less than 5%. The R^2 values for predicting the electrical energy consumption and COP were found to be 0,9459 and 0,9999964, respectively. Through a sensitivity analysis, the volume of milk proved to be the most important factor influencing energy consumption of the on-farm DXBMC as well as its COP. The application of ANN models for predicting the performance of a bulk milk cooler is useful for dairy farms as they require thorough energy management and strategies for the efficient operation of a milk cooling system since it is one of the major operations that consumes much energy.

Keywords: Direct expansion bulk milk cooler; artificial neural network; coefficient of performance; dairy milk cooling; energy consumption

Voorspelling van die prestasie van ’n op-die-plaas-tipe direkteuitsetting-grootmaatmelkverkoeler met behulp van kunsmatige neurale netwerke: Die prestasie van ’n op-die-plaas-tipe direkteuitsetting-grootmaatmelkverkoeler (“DXBMC” na aanleiding van die bekende Engelse benaming waarmee daarna verwys word) is voorspel deur die gebruik van kunsmatige neurale netwerkmodelle. Data is op ’n bestaande plaas ingesamel gedurende die tydperk April 2016–Maart 2017. Die data is in MATLAB opgelaai om kunsmatige neurale netwerke (KNN’e) te ontwikkel en die energieverbruik en die prestasiekoëffisiënt (PK) van die DXBMC te simuleer. Die data is 70:15:15 verdeel, wat onderskeidelik opleidings-, validerings- en toetsdatastelle verteenwoordig. Twee KNN’e is vir die energieverbruik en die PK onderskeidelik ontwikkel. Verskeie neurale netwerke is geskep en in ’n sistematiese prosedure opgelei. Seleksie van die beste kombinasie van voorspellers vir die modelle is gebaseer op die bepaaldheidskoëffisiënt (R), wortel van gemiddelde kwadraatfout (WGKF) en gemiddelde absolute persentasiefout (GAPF). Die belangrikheid van die insette vir die uitset is ook afgelei. Die resultate het hoë akkuraatheid in voorspellings van die energieverbruik en die PK getoon, aangesien die waardes van die GAPF minder as 5% was. Daar is gevind dat die R^{2}- waardes vir die voorspelling van die elektriese energieverbruik en PK onderskeidelik 0,9459 en 0,9999964 is. Deur ’n sensitiwiteitsanalise het dit geblyk dat die volume melk die belangrikste faktor is wat die energieverbruik van ’n op-die-plaas-tipe DXBMC sowel as die PK daarvan beïnvloed. Die toepassing van KNN-modelle vir die voorspelling van die prestasie van ’n grootmaatmelkverkoeler is nuttig vir melkplase, aangesien hulle deeglike energiebestuur en strategieë benodig vir die doeltreffende werking van ’n melkverkoelingstelsel, want dit is een van die belangrikste bedrywighede en verbruik baie energie.

Sleutelwoorde: Direkteuitsetting-grootmaatmelkverkoeler; kunsmatige neurale netwerk; prestasiekoëffisiënt; suiwelmelkverkoeling; kragverbruik

Introduction

The use of artificial intelligence (AI) systems and machine learning techniques in the refrigeration field has been on the rise over the years to solve some complex problems, as reported by Mohanraj *et al.* (2012). The AI systems include ANN, fuzzy logic and a fusion of many systems, which combine two or more techniques (Kalogirou, 2003; Mellit & Kalogirou, 2008; Mohanraj *et al.,* 2012). ANNs are fast and simple models that can solve problems of a complex nature in terms of interrelationships among variables through extracting the nonlinear relationships between variables. They are biologically inspired computational models, have been used to portray complicated non-linear interrelationships among a multitude of factors, and they also mimic the brain function in a computerised way based on the transmission and receiving of signals (Agatonovic-Kustrin & Beresford, 2000; Kalogirou, 2003; Mellit & Kalogirou, 2008; Mohanraj *et al.,* 2012). Figure 1 presents an illustration of an artificial neuron.

ANNs are built from interconnected neurons that process information from the inputs to the desired outputs. The generation of the output from the inputs is facilitated by the connection weight, which links the inputs to the summation and transfer functions. Based on the literature, different ANN architectures like multilayer feedforward networks (MLFFN), generalised regression neural networks (GRNN), adaptive neuro-fuzzy interface systems (ANFIS) and radial biased function networks (RBFN), amongst others (Jang, 1993; Kalogirou, 2003; Mellit & Kalogirou, 2008; Mohanraj *et al.,* 2012), have been applied to refrigeration systems. Over the years, research has been conducted on a variety of refrigeration systems using different approaches and ANN model architectures. Ertunc and Hosoz (2006) conducted a study on a cascade refrigeration system where MLFFN was applied to predict its performance. The experimental results were closely emulated by the ANN model. An investigation by Redy *et al.* (2020) focused on using multiple regression analysis (MRA) and ANN to predict the performance of a domestic refrigerator. The study concluded that performance prediction using the ANN model was very accurate. In another study, Opalic *et al.* (2020) established an ANN-based technique for modelling the operation of a cooling system that used CO_2 as a refrigerant in an industrial setup. Ribault *et al.* (2019) used an ANN to forecast temperature for a cold room where a dynamic programming algorithm was used. Also, dimensionless correlation and ANN models were developed by Gill and Singh (2018) to predict the mass flow rate in a vapour compression refrigeration system. In several other studies, ANNs were used widely on various refrigeration systems to predict energy (power) consumption, cooling capacity and coefficient of performance (Swider *et al.,* 2001; Ertunc & Hosoz, 2006; Navarro-Esbrı *et al.,* 2007; Escobedo-Trujillo *et al.,* 2016; Barroso-Maldonado *et al.,* 2017; Aprea *et al.,* 2017). Numerous techniques for performance prediction of vapour compression refrigeration systems based on simulations and modelling have been presented by Ding (2007).

Studies on the application of machine learning have also been conducted on dairy farms. Shine *et al.* (2018) presented a study where a range of machine learning algorithms were applied to the prediction of electricity and on-farm direct water consumption on pasture-based commercial Irish dairy farms. Sefeedpari *et al.* (2014) implemented an adaptive neural-fuzzy inference system to model output energy based on energies of fossil fuels and electricity inputs for dairy farms in Iran. It is worth mentioning that the accuracy of model performance is useful to predict energy usage in a dairy enterprise. It forms the basis for improved energy efficiency planning strategies towards the improved operation of the farm. Based on the reviewed literature, ANN models have proved to have high accuracy in predicting the performance of refrigeration systems. However, to the author's knowledge the application of ANN to bulk milk coolers is only covered to a limited extent in literature.

The main objective of the present study is to develop ANN models for predicting the performance of an on-farm DXBMC. Application of the developed ANNs to the cooling energy requirements on a dairy farm will provide insight into the cooling performance of the DXBMC. This insight will allow for optimisation of the cooling system, performance enhancement, maintenance scheduling as well as energy savings where milk temperature has to be kept at the best possible minimum. By

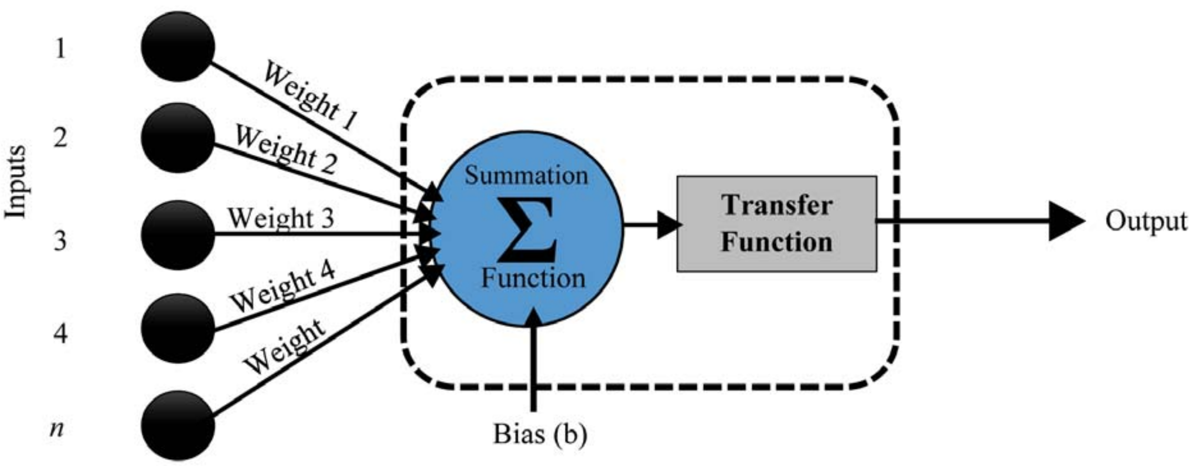

Figure 1: Artificial neuron adapted from Kalogirou (2003), and Mellit and Kalogirou (2008)

using the developed ANN model, the performance of the DXBMC is determined in terms of the energy consumption and the COP during the daily milking schedule of a dairy farm.

Materials and Methods

Data collection

Data was collected at an existing farm according to the procedures laid out by Mhundwa *et al.* (2017) for the period April 2016–March 2017. A twice a day milking routine was observed throughout the year, that is, in the early morning (05:00–07:00) and late afternoon (15:00–17:00). The schematic layout of the experimental procedure is shown in Figure 2.

Theory and calculations

The thermal heat removed from the milk by the DXBMC is calculated in Equation 1:

Equation 1

$$Q = \frac{mC_{pm}(T_{mi} - T_{mf})}{3600} \quad (1)$$

Where
m = mass of milk delivered to the bulk milk cooler (kg)
C_{pm} = specific heat capacity of milk (3,93 kJ/kg °C)
T_{mi} = milk inlet temperature delivered to the DXBMC
T_{mf} = final milk temperature in the DXBMC (4°C)

Equation 2 indicates the COP calculation for the DXBMC:

Equation 2

$$COP = \frac{E}{Q} \quad (2)$$

Where
E = measured energy consumption for the DXBMC (kWh)

Formulation and training of the ANNs

The collected data for a year (April 2016–March 2017) was submitted to MATLAB to develop artificial ANNs and simulate the energy consumption and COP of the DXBMC. The data was split 70:15:15, representing training, validation and testing datasets respectively. Two ANN models were developed, that is, for the energy consumption and COP respectively. For this study, an MLFFN trained by the Levenberg Marquardt (LM) was applied. Several neural networks were created and trained in a systematic procedure. The basic neural networks are represented in Figure 2. The basic architectural structure of an ANN network is separated into three layers, namely the input, hidden and output layers (Figure 2). The input layer comprised the input variables, in this study the milk volume (Vmilk), milk temperature (Tmilk), ambient temperature (Tamb), room temperature (Troom) and relative humidity (RH), which were considered for the energy consumption ANN (ANN_E), while energy consumption, Vmilk, Tmilk, Tamb, Troom and RH were used for the COP ANN (ANN_{COP}). Table I shows the details of the developed ANNs.

To evaluate the best combination of input parameters to predict the energy consumption and the COP of the DXBMC, the forward stepwise regression selection method was applied. In this method, all the variables are taken as inputs to the ANN to determine the best combination of variables for predicting the energy consumption and the COP respectively. Selection of the best combination was based on R, RMSE and MAPE. Figure 3 illustrates the neural network architecture for energy consumption and the COP of a DXBMC.

Simulation, validation and error analysis

Performance of the network was tested using R while the reliability of the model was determined through the MAPE and the comparison between the measured and predicted values was deduced by the RMSE. The following equations show how R, MAPE and RMSE are calculated:

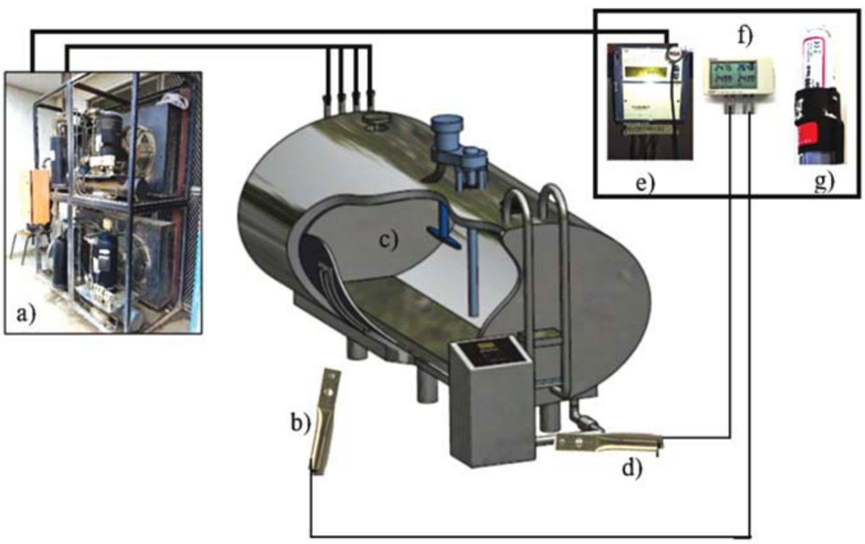

Figure 2: Experimental layout of the DXBMC **a**) condensing unit, **b**) room temperature sensor, **c**) bulk milk cooler, **d**) milk temperature sensor, **e**) power meter, **f**) data loggers, **g**) relative humidity and ambient temperature sensor (Source: Mhundwa *et al.*, 2018)

$$R = \frac{\sum_{i=1}^{n}(M_i - \overline{M}_i)(P_i - \overline{P}_i)}{\sqrt{\sum_{i=1}^{n}(M_i - \overline{M}_i)} \times \sqrt{\sum_{i=1}^{n}(P_i - \overline{P}_i)}} \quad (3)$$

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{M_i - P_i}{M_i}\right|}{n} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - P_i)^2} \quad (5)$$

Where for equations 1, 2 and 3:
M = measured value
P = predicted value
n = number of data

Each predictor for the best performing ANN model was tested to determine its usefulness in predicting the outputs (energy consumption and COP). This was done by removing one predictor at a time and checking the increase and decrease in the MAPE, RMSE and R.

Ranking of predictors' importance in respect of output

The connection weight approach was used to rank the model inputs according to their effect on the output. According to Olden and Jackson (2002) and Olden *et al.,* (2004), the connection weights method determines the relative importance of predictors of an ANN model as a function of the NN weights. This method was selected based on its accuracy as it is derived from the weights of the ANN (De Oña & Garrido, 2014).

Measurement and calculation uncertainty

Experimental data and derived calculations are governed by the accuracy of the instruments used to collect the data (Coleman & Steele, 2018). In this study, temperature, relative humidity, ambient temperature and power measurements had tolerances of ± 0,15°C, ± 2,5%, ± 0,21°C and 1% respectively (Mhundwa *et al.,* 2018).

Results and Discussion

The performance of a DXBMC in terms of energy consumption and COP can be predicted using the ANN model with the input parameters as shown in Figure 1. The number of neurons considered for this study was between two and 12 for both the energy consumption and COP prediction, and the network was trained several times so as minimise the error between the predicted values. Table II shows a correlation matrix for the variables.

The correlation coefficients presented in Table II were deduced from Pearson's method. It can be observed that most of the correlation coefficients are low except for Troom and Tamb (0,960), Troom and RH (–0,829) and Tamb and RH (–0,877). This is due to the inverse and direct interplay of various weather-related variables. It should be noted that high correlations between variables can result in overfitting of a model.

Table I: Summary of the developed ANNs

ANN_E description			ANN_{COP} description
Structure		Number of neurons	
	Inputs	1. Milk temperature	1. Milk temperature
		2. Milk volume	2. Milk volume
		3. Room temperature	3. Room temperature
		4. Relative humidity	4. Relative humidity
		5. Ambient temperature	5. Ambient temperature
			6. Energy consumption
	Hidden layer	Number of neurons = 2–12	
	Output	Number of neurons = 1 (energy consumption)	Number of neurons = 1 (COP)
Transfer function	Hidden neurons	Tangent sigmoid	
	Output neurons	Pure linear	
Training method		Training goals: minimum mean square error	
		Epoch: 1 000 times	
		Algorithm: Levenberg Marquardt	
Database size		180	180
Database partitioning		Training: 70%	
		Validation: 15%	
		Test: 15%	

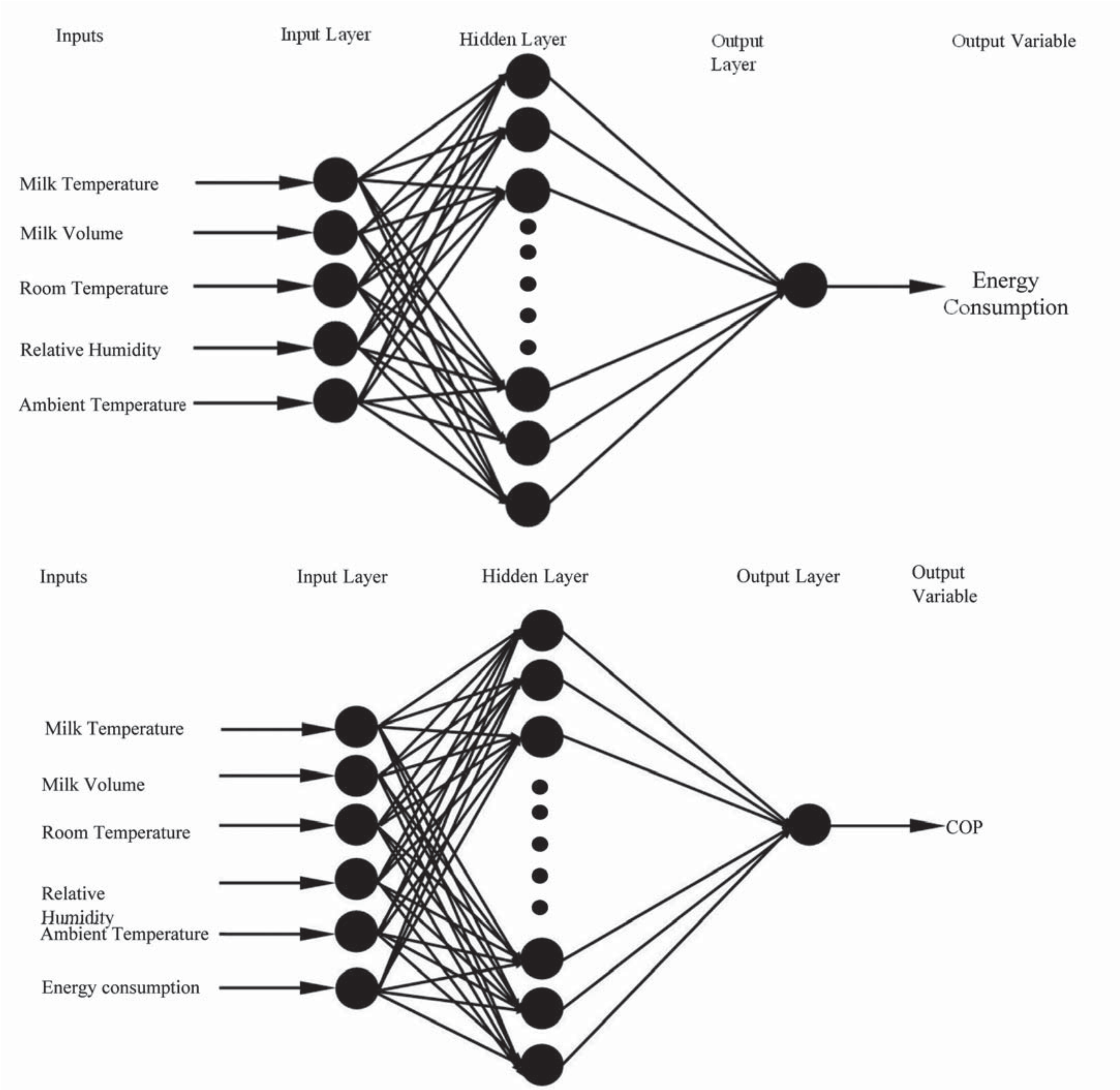

Figure 3: Neural network architecture for energy consumption and the COP

Table II: Correlation matrix for the variables

Variables	Vmilk	Tamb	RH	Tmi	Troom
Vmilk	1				
Tamb	–0,497	1			
RH	0,395	–0,877	1		
Tmi	0,041	0,410	–0,491	1	
Troom	–0,472	0,960	–0,829	0,445	1

ANN Models

ANN models were developed with all predictors, and Table III and Table IV illustrate the performance indicators.

As indicated in Table III, Vmilk constitutes the bulk of the predictive information for energy consumption. This is due to its high correlation (0,84) to energy consumption. It can be observed that adding Tmilk as one of the predictors led to improved performance of the ANN model. The RMSE and MAPE decreased by 43,56% and 44,15% respectively, while R increased by 9% with 12 neurons. Further addition of Troom to the predictors reduced the RMSE by a further 13% and MAPE by 7%, and R increased to 0,9725, from 0,9636. By adding Tamb as one of the predictors, reduced performance is noticeable, with an

Table III: ANN_E models

Model	Predictors	NN	RMSE (kWh)	MAPE (%)	R
1	Vmilk+Tmilk+Troom+Tamb+RH	6	5,6496	4,1621	0,9726
2	Vmilk+Tmilk+Troom+Tamb	8	6,0752	4,2886	0,9679
3	Vmilk+Tmilk+Troom	8	5,6319	4,1473	0,9725
4	Vmilk+Tmilk	12	6,4736	4,4465	0,9636
5	Vmilk	8	11,4689	7,9619	0,8805

Table IV: ANN_{COP} models

Model	Predictors	NN	RMSE	MAPE (%)	R
1	Energy consumption+Vmilk+Tmilk+Troom+Tamb+RH	12	0,00037208	0,00919173	0,9999982
2	Energy consumption+Vmilk+Tmilk+Troom+Tamb	10	0,00057565	0,0076484	0,99999573
3	Energy consumption+Vmilk+Tmilk+Troom	12	0,00031892	0,00953144	0,99999867
4	Energy consumption+Vmilk+Tmilk	8	0,00025759	0,00838367	0,99999916
5	Energy consumption+Vmilk	10	0,04999166	1,65165818	0,96706873
6	Energy consumption	10	0,1812502	6,3688037	0,37563743

increase in RMSE to 6,075 kWh as well as a slight reduction in R to 0,9679. This was because of the interaction effect between Tamb and Troom due to location of the DXBMC, as reported in Mhundwa *et al.* (2017), as a well as the redundancy caused by the high correlation coefficient between the two variables as shown in Table III. Addition of RH slightly increased R to 0,9726, and reduced RMSE and MAPE by 7% and 3% respectively. The performance of ANN model 1 (Table III) indicates that all five the input variables led to better performance in terms of R (0,9726). The performance of model 1 and model 3 are closely related in terms of R. However, the RMSE and MAPE are slightly lower for model 3.

The deduction from the results in Table IV are that using all the predictors in the model leads to a better performance of the network. Removing RH as one of the predictors reduces R by less than 0,00025%, with an increase in RMSE and a decrease in MAPE. The performance of the network after removal of Tamb is such that R and MAPE increase, while RMSE decreases. A network with energy consumption, Vmilk and Tmilk exhibits the best performance with the highest R (0,99999916) and the lowest RMSE (0,00025759). Energy consumption and Vmilk contain most of the predictive information for the COP of a DXBMC. It can be deduced that adding Vmilk as one of the predictors led to improved performance of the ANN model. The RMSE and MAPE decreased by 72,42% and 74,07% respectively, while R increased by 157,45%. Further addition of Tmilk to the predictors reduced the RMSE by a further 99,48% and MAPE by 99,49%, and R increased from 0,96706873 to 0,99999916. Besides, by adding Troom as a predictor, reduced performance is noticeable with an increase in RMSE as well, and a slight reduction in R. Figure 4 and Figure 5 illustrate the ANN predicted energy consumption, and the actual energy consumption and COP for a DXBMC.

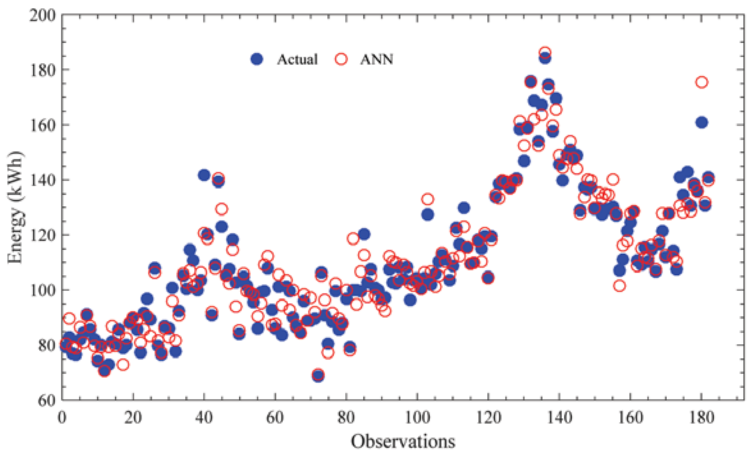

Figure 4: ANN-predicted energy consumption and actual energy consumption for a DXBMC

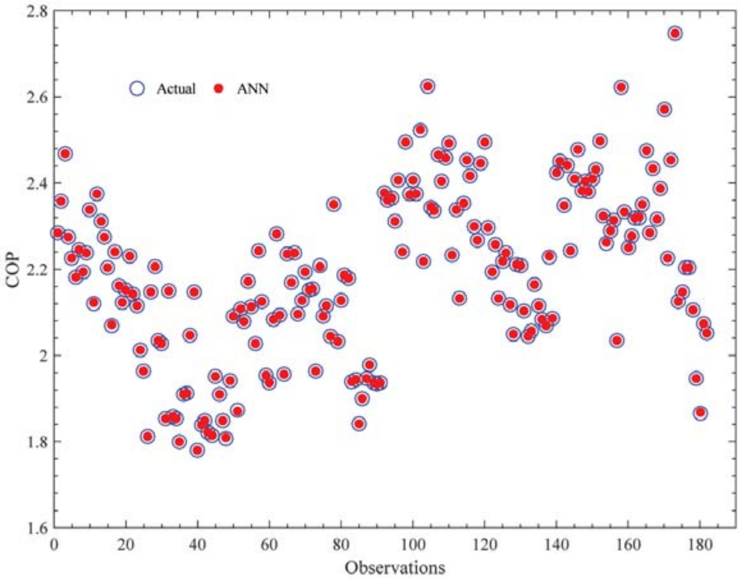

Figure 5: ANN-predicted energy consumption and actual COP for a DXBMC

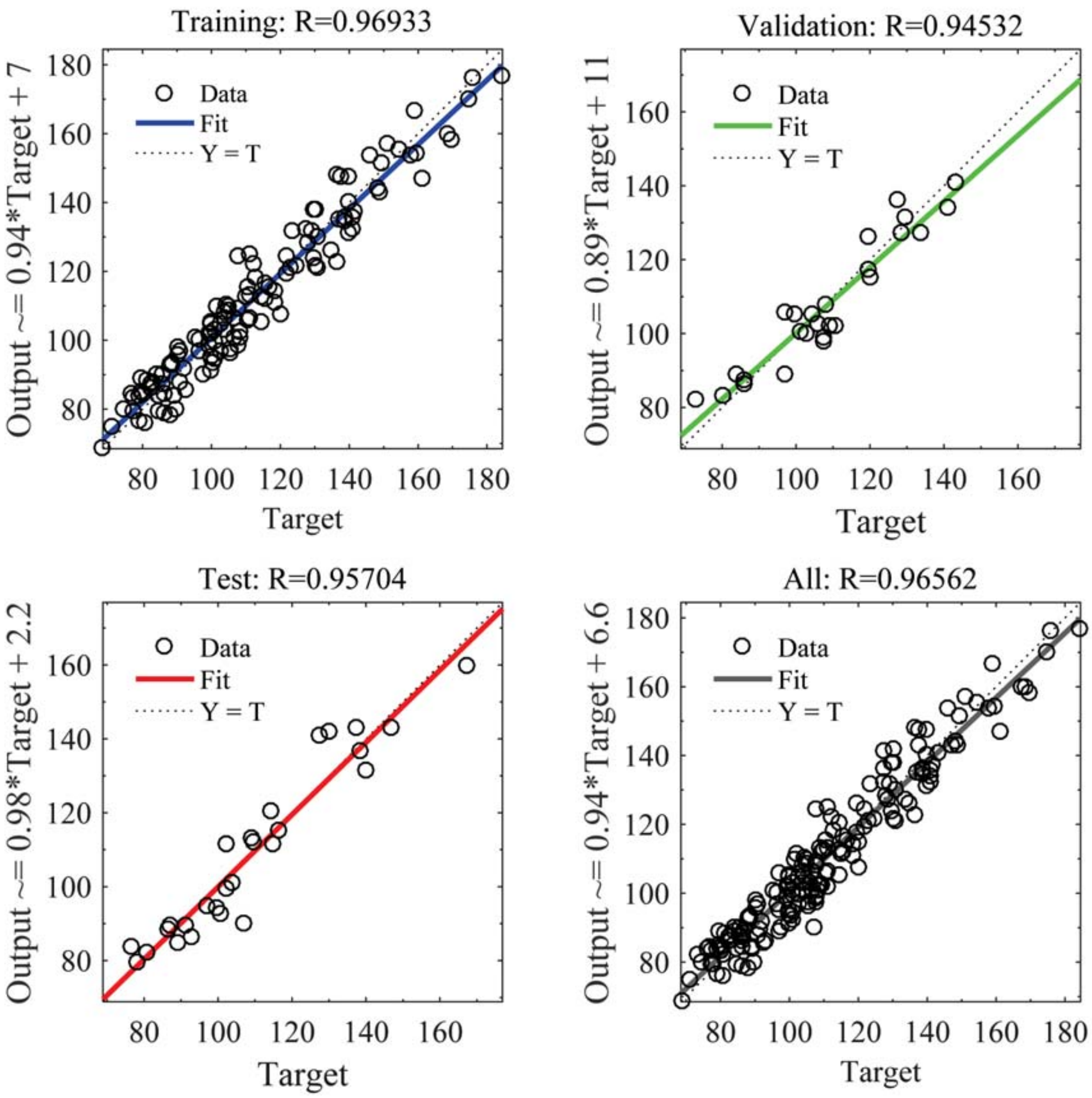

Figure 6: ANN_E regression plots

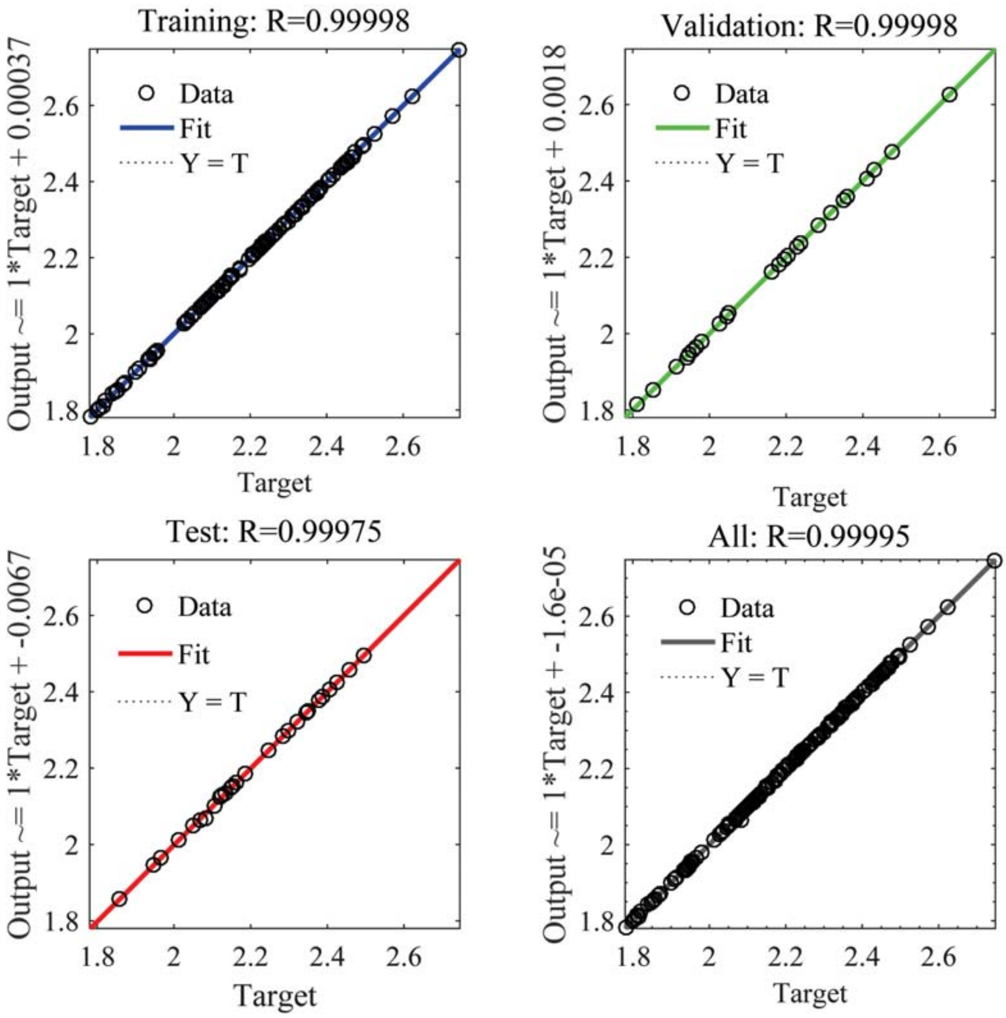

Figure 7: ANN_{COP} regression plots

Comparison of the sampled experimental data and ANN prediction results for energy consumption and COP are shown in Figures 4 and 5. The plots give a visual representation of the prediction errors. The comparisons show that the ANNs significantly represented the experimental data; thus, the results confirm the remarkable capability of the ANN models to predict energy consumption and COP. Figures 6 and 7 illustrate the regression plots for the ANN_E and ANN_{COP}.

The four plots in Figure 6 and Figure 7 represent the regression plots for training, validation, testing and all data for the energy consumption and COP, respectively. The perfect result of outputs = targets is represented by the dotted black line, while the continuous lines are representing the best-adapted linear regression between outputs and targets (Figure 6 and Figure 7). The target and output data generated by the artificial neural network form the corresponding horizontal and the vertical axes. It can be deduced that the training data have a good fit with R = 0,97989, meaning the output data of the ANN imitated the desired target data. The results also show that the R values were greater than 0,95 for the validation and test data. Likewise, it can be construed from Figure 6 that the training data indicate a good fit, with R = 0,99999. The validation and test results also yielded R values above 0,99. The result indicated that the energy consumption and COP of a DXBMC were successfully predicted with high accuracy by a single-layered ANN. Figures 8 and 9 show the validation performance of the developed ANNs.

The creation of the ANNs' structure, used in the modelling of the energy consumption COP, was performed with 10 epochs and 12 epochs respectively. The best validation agreement at mean squared error (MSE) = 34,5666 was reached at the 10th epoch, where R^2 = 0,9759, while the MSE = $1{,}851\times10^{-6}$ was reached at the 12th epoch, at R^2 = 0,9999964 for the COP. Figures 8 and 9 additionally illustrate the practicality of the training results for the ANNs. This is seen by the negligible errors between the training and validation datasets. Of note is that, upon further training of the ANNs, these errors did not change meaningfully. Figures 10 and 11 illustrate the error histogram for ANN_E and ANN_{COP}.

The ANN_E and ANN_{COP} model errors were deduced from the difference between the predicted values and the actual values. In that regard, the positive errors indicate that the predicted value for the ANN underestimated the actual value, while negative errors indicate that the predicted value overestimated the actual value. Analysing Figures 10 and 11 we can observe that the majority of the errors are located next to the zero-error line. Thus, the prediction given by the trained ANN is quite acceptable.

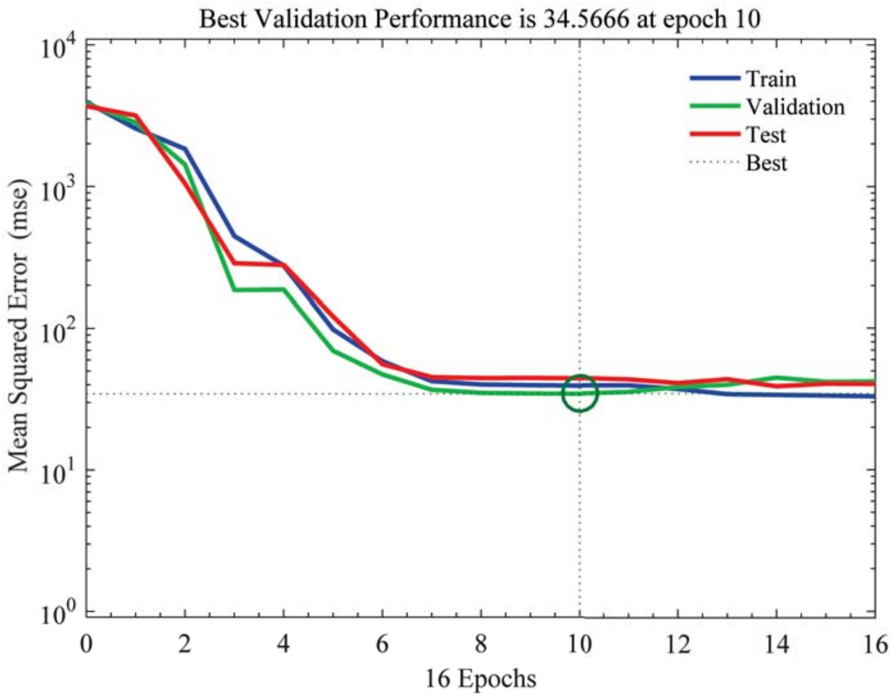

Figure 8: ANN_E validation performance

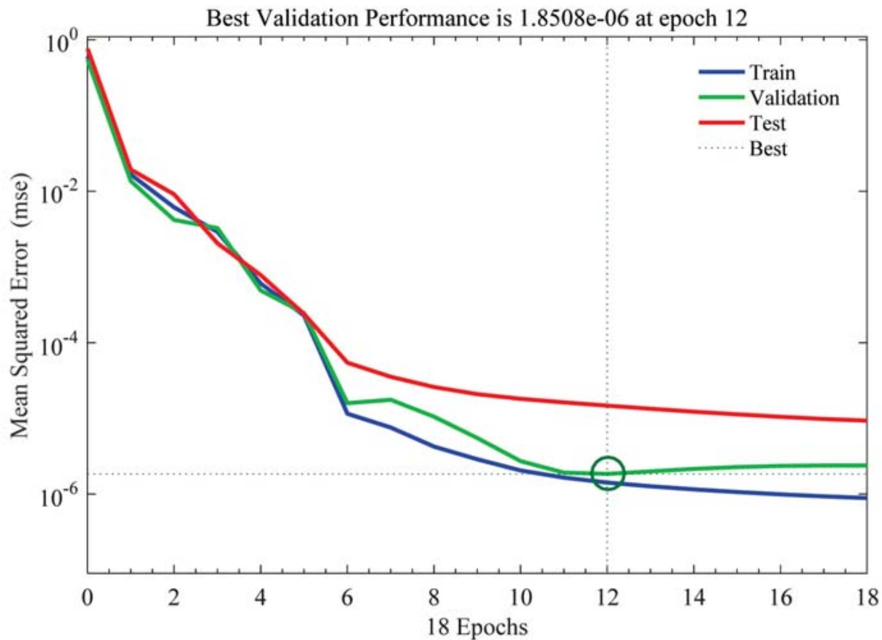

Figure 9: ANN_{COP} validation performance

Relative importance of the predictors

The index of relative importance (R_i) was deduced for each of the predictors for determining the relation of the predictor to the response as illustrated in Figures 12 and 13.

As indicated in Figure 12, Vmilk, Tmilk and Troom varied in the positive direction, whereas RH and Tamb varied in the negative direction at almost the same magnitude. This implies that Vmilk, Tmilk and Troom had a positive relationship with energy consumption. Accordingly, Vmilk had the most significant contribution to energy consumption (R_i= 1,902) followed by Troom (R_i = 1,378). The results depict that the energy consumption of the DXBMC was more sensitive to the change in Vmilk. According to Figure 13, energy consumption is the most crucial variable in predicting COP of a DXBMC (R_i = –5,817), followed by Vmilk (R_i = 3,350) and Tmilk (R_i = 1,284). Troom, Tamb and RH had the least contribution to the COP of the system. The COP of the DXBMC was the more sensitive to the change in the energy consumption followed by Vmilk and Tmilk. Furthermore, it should be mentioned that the COP was least sensitive to Troom, Tamb and RH. The findings from this study suggest that Vmilk and Tmilk are significant predictors for the performance of a DXBMC. As such, optimising Vmilk and Tmilk will contribute to the efficient operation of the DXBMC. Mostly,

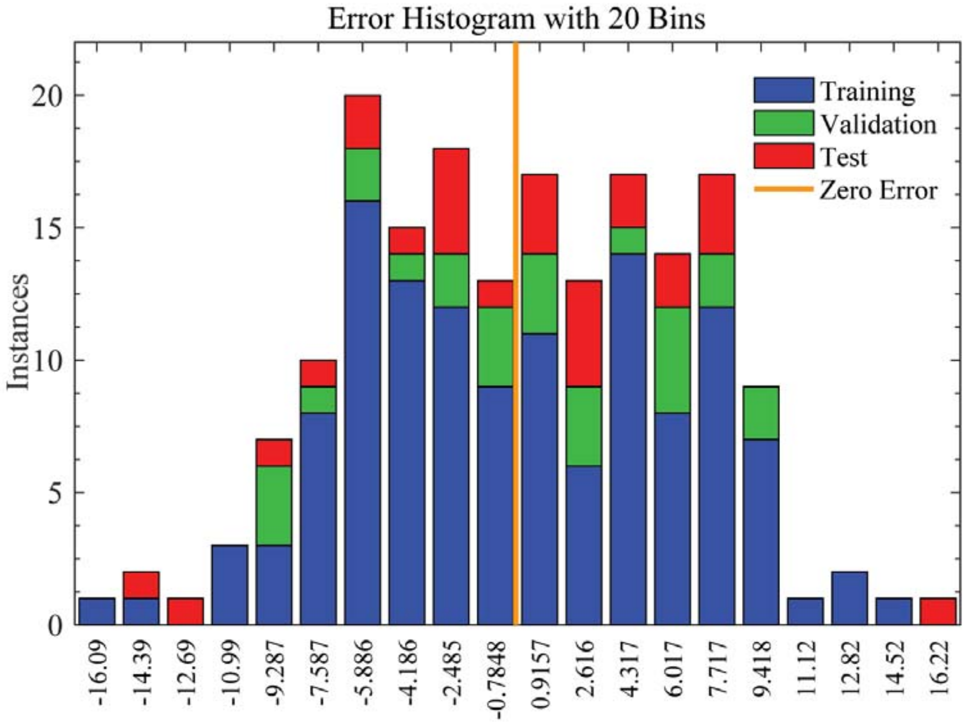

Figure 10: Error distribution for ANN_E

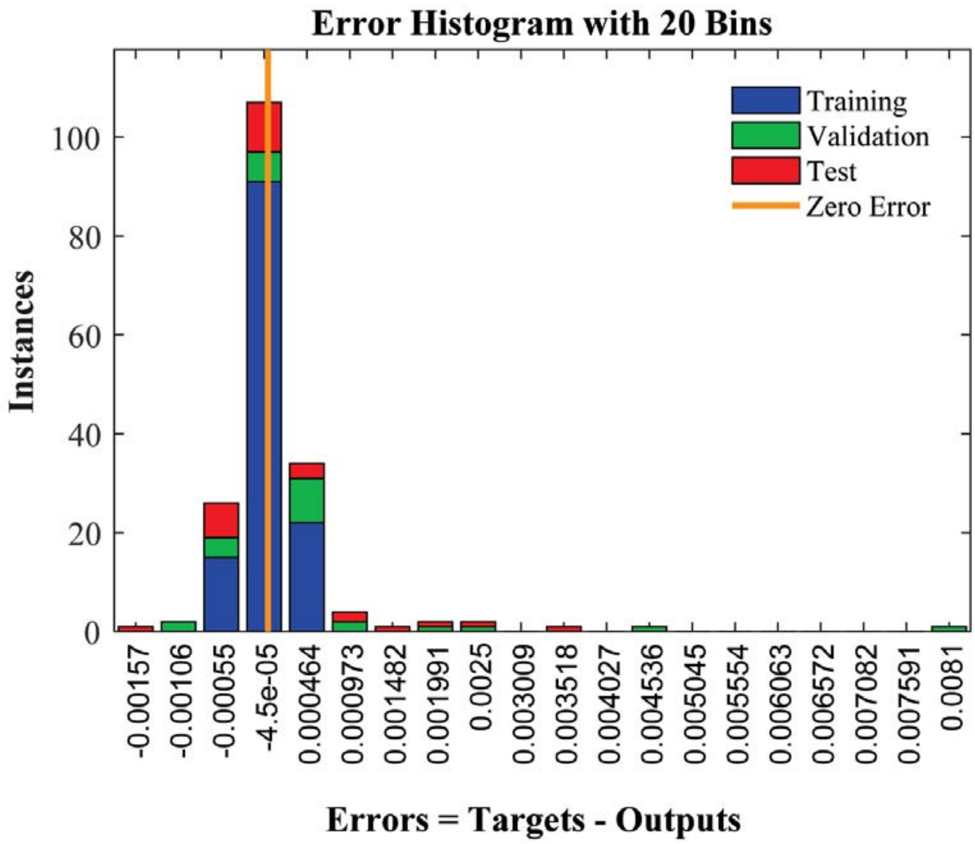

Figure 11: Error distribution for ANN_{COP}

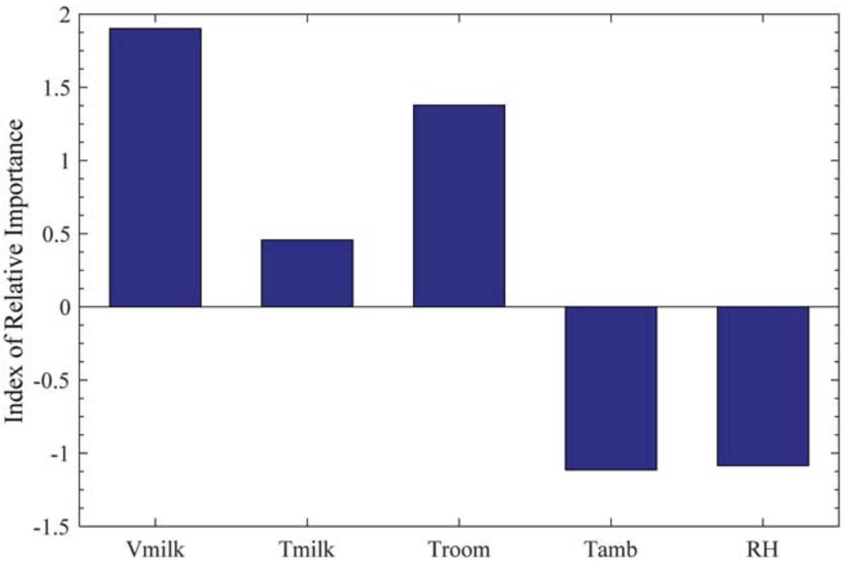

Figure 12: Relative Importance of predictors for ANN_E

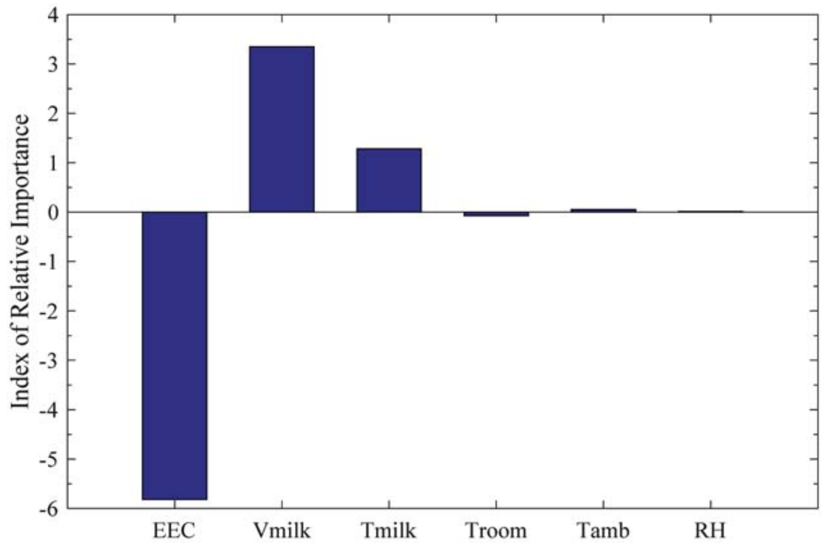

Figure 13: Relative Importance of predictors for ANN_{COP}

raw milk leaves the cow at a temperature of 35–37 °C and rapid cooling to a temperature of 4 °C renders it safe (Lewis and Heppell, 2000; Holm *et al.,* 2004; Upton *et al.,* 2010). This suggests that in a direct milking-to-refrigeration system, milk is delivered to the DXBMC at approximately 32 °C (Mhundwa *et al.,* 2018); hence energy consumption will also increase. On the other hand, previous studies (Peebbles *et al.,* 1993; O'Keeffe, 2007; Murphy *et al.,* 2013; Mhundwa *et al.,* 2016) revealed that milk pre-cooling using groundwater as the coolant can reduce the temperature of the milk to an average of 19,9 °C. These studies showed that there was a 50,3% decrease in energy consumption, and the use of a raw milk precooler enhanced the efficiency of the DXBMC, which led to a significant reduction in energy consumption. Intuitively, Tmilk can be effectively controlled on a dairy farm. However, herd size and selection of cattle breeds, farm size and quality of feed may in turn have an impact on the volume of milk (Vmilk) produced (Dillon *et al.,* 2003; Franzoi *et al.,* 2020).

Conclusion

The performance of an on-farm DXBMC was analysed in a bid to predict energy consumption and coefficient of performance through models that were based on ANNs trained with a database obtained from data that was measured on an existing dairy farm. The findings from the study are summarised as follows:

1. The result indicated that the energy consumption and COP of a DXBMC could be predicted by a single-layered neural network
2. The accuracy given by the ANN models are acceptable and can be used for on-farm DXBMCs to monitor and optimise the milk cooling operations.
3. The index of relative importance of the predictors show that Vmilk and Tmilk are the most essential variables in predicting both energy consumption and COP of a DXBMC.
4. The energy consumption is mostly sensitive to the Vmilk, whereas the COP is mostly sensitive to energy consumption.

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