South African Journal for Science and Technology
ISSN: (Online) 2222-4173, (Print) 0254-3486

Mathematical modelling of the coefficient of performance of an on-farm direct expansion bulk milk cooler: A multiple linear regression approach

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Dates:
Received: 10/02/21
Accepted: 27/07/21
Published: 21/09/21

How to cite this article:
Russel Mhundwa, Michael Simon, Mathematical modelling of the coefficient of performance of an on-farm direct expansion bulk milk cooler: A multiple linear regression approach, *Suid-Afrikaanse Tydskrif vir Natuurwetenskap en Tegnologie* 40(1) (2021). https://doi.org/10.36303/SATNT.2021.40.1.840

'n Afrikaanse vertaling van die manuskrip is aanlyn beskikbaar by http://www.satnt.ac.za/index.php/satnt/article/view/840

In this study, a method for predicting the coefficient of performance (COP) of an on farm-direct expansion bulk milk cooler (DXBMC) is presented in the form of a multiple linear regression (MLR) model. The experimental data used to build and develop the model was collected from a 21 m^3 DXBMC utilising a data acquisition system comprising temperature sensors, an ambient temperature and relative humidity sensor, and a power meter. The study revealed that the COP of an on-farm DXBMC could be predicted using an MLR model with high accuracy. The R2 value for predicting the COP was found to be 0.957. Furthermore, the developed model is statistically significant as was deduced by significance $p = 1.31 \times 10^{-120}$. The model can predict the COP with relatively high precision as indicated by a low root mean squared error (RMSE) = 0.0406 with a standard error for using the model to predict the COP of 0.0392 implying the experimental data produces a good fit. The ReliefF algorithm and 2D simulation plots indicated that energy consumption and volume of milk were primary contributors to the COP. In contrast, milk temperature, ambient temperature and relative humidity were secondary contributors. The study found that electrical energy is the most critical factor influencing the COP of the on-farm DXBMC. Thus, energy efficiency initiatives in dairy farms would help to optimise energy consumption.

Keywords: direct expansion bulk milk cooler, regression, coefficient of performance, dairy milk cooling, modelling

Wiskundige modellering van die prestasiekoëffisiënt van ʼn direkte-uitbreiding grootmaatmelkverkoeler op ʼn plaas: ʼn Veelvoudige lineêre regressie-benadering: In hierdie studie word ʼn metode vir die voorspelling van die prestasiekoëffisiënt (COP) van ʼn direkte uitbreiding op n grootmaatmelkverkoeler (DXBMC) aangebied in die vorm van ʼn meervoudige lineêre regressie (MLR) model. Die eksperimentele data wat gebruik is om die model te bou en te ontwikkel, is versamel vanaf ʼn DXBMC van 21 m^3 met behulp van ʼn dataverwerwingstelsel wat temperatuursensors, ʼn omgewingstemperatuur- en relatiewe humiditeitsensor en ʼn kragmeter bevat. Die studie het aan die lig gebring dat die COP van ʼn DXBMC op die plaas met hoë akkuraatheid voorspel kan word. Daar is gevind dat die R^2-waardes vir die voorspelling van die COP 0.957 is. Verder is die ontwikkelde model statisties beduidend, met n p-waarde van $1{,}31 \times 10^{-120}$. Die model kan die COP met ʼn relatiewe hoë akkuraatheid voorspel, soos aangedui deur ʼn lae wortel gemiddelde kwadraatfout (RMSE) wat 0,0406 is met ʼn standaardfout vir die gebruik van die model om die COP van 0,0392 te voorspel, wat aandui die eksperimentele data lewer ʼn goeie pasvorm. Die ReliefF-algoritme en 2D-simulasiegrafieke het aangedui dat energieverbruik en volume melk primêr bydra tot die COP. Daarenteen was melktemperatuur, omgewingstemperatuur en relatiewe humiditeit sekondêre bygedraende faktore. Die studie het bevind dat elektriese energie die belangrikste faktor is wat die COP van die DXBMC op n plaas beïnvloed. Dus kan energie-doeltreffendheidsinisiatiewe in melkboerderye help om die energieverbruik te optimaliseer.

Sleutelwoorde: Direkte uitbreiding van grootmaatmelkkoeler, regressie, prestasiekoëffisiënt; verkoeling van melk; modellering

Introduction

The number of milk producers in South Africa decreased by 57% between January 2011 and January 2020. However, between 2011–2019, milk production and milk production per producer increased by 26% and 291%. In 2019, the Western Cape Province, Eastern Cape and KwaZulu-Natal contributed about 87.5% of the total milk produced in the country. The number of cows in milking varies widely among producers with the Eastern Cape Province having the highest average of 814 cows per producer (International Farm Comparison Network, 2019). Interestingly, 98% of the raw milk in South Africa has to be delivered for further processing, hence handling of milk at the dairy farm is crucial to avoid contamination. In a typical processing plant, milk undergoes a series of processing activities before being rendered safe for human consumption. These entail handling raw milk, clarification, homogenisation, pasteurisation and chilling (Modi and Prajapat, 2014). This suggests that the milk quality on the dairy farm from milking to storage is of paramount importance. Dairy farming is an energy-intensive enterprise and involves various processes: ventilation, lighting, water heating, milk cooling, transportation and irrigation where a considerable amount of energy is required. Amongst these processes, milk cooling constitutes approximately 20–36% of the total energy consumption (Peterson, 2008; Upton et al., 2013). Thus, the cooling system's efficient operation is crucial for any dairy farm as it ensures acceptable product quality.

Specifically, milk is supposed to be cooled rapidly from 35 °C–37 °C to a storage temperature of 4 °C to stop microbial activity (Lewis and Heppell, 2000; Holm et al., 2004; Upton et al., 2010). The cooling can be done directly or through pre-cooling (Saravacos and Kostaropoulos, 2002; Mhundwa, 2017). Subsequently, the milk is stored in the DXBMC and in most dairy farms storage usually takes at most two days before it can be collected by refrigerated tankers, which serve to maintain the milk at 4 °C. The performance of a refrigeration system is determined by the coefficient of performance (COP); it signifies the heat removed from the milk per unit of energy used by the BMC to remove the heat. The COP strongly depends on outside temperature and required milk temperature. On a dairy farm, higher COPs equate to higher efficiency, lower electrical energy consumption and thus lower operating costs for the farmer. The COP of a DXBMC can range from 2.6 to 5 (Mhundwa et al., 2017). Like any other system that operates on the vapour compression refrigeration cycle (VCRC), it is governed by its design and the operational conditions and location. However, to achieve an optimum COP for the DXBMC, professional installation of the system is essential and the day to day operation of the DXBMC. The COP of the DXBMC can be improved by pre-cooling and waste heat recovery from the condenser and using water-cooled condensers instead of air-cooled condensers (Sapali et al., 2014). Various studies on the COP of refrigeration equipment can be found in literature, ranging from domestic, industrial and transportation. Tian et al. (2019) developed a method for predicting the COP of an on-site screw chiller. Their study used artificial neural network (ANN) as the modelling technique. Opalic (2020) also developed an ANN modelling of CO_2 refrigerant cooling system COP for a warehouse. Zhu et al. (2019) Zhu et al. (2013) propose a generic simulation model for performance and control analysis. Laidi and Hanini (2013) developed an optimal solar COP prediction of solar-assisted adsorption refrigeration system through ANN modelling; Artuso et al. (2020) modelled a new cooling performance unit for refrigerated transportation. Nikbakhti et al. (2020) developed a lumped-parameter thermodynamic model for performance analysis of integrated adsorption and absorption refrigeration system. Lee and Lu (2010) evaluated the performance of vapour-compression water chillers. Their study focused on using empirically-based models achieved using the least-squares method. The developed models predicted the energy performance of the water chillers. It is worth mentioning that the COP performance of a direct expansion bulk milk cooler is inadequately reported in the literature. This study seeks to predict the COP performance of a DXBMC through multiple linear regression modelling techniques. This study aims to develop a mathematical model that captures the performance of an on-farm direct expansion DXBMC in terms of its COP. The developed model for the on-farm DXBMC helps visualise the impact of the milk loading and environmental conditions on the COP. Through the ReliefF algorithm, the influence and contribution of each predictor variable to the COP were derived. Furthermore, each predictor's effects on the COP were deduced through the 2D simulation plots that allow varying single predictors, while the others are held constant.

Materials and methods

System description

The study took place on an existing dairy farm in the Eastern Cape Province of South Africa with a 21 m^3 DXBMC and an average of 500 cows-in-milking. The farm had its milking done twice every day (AM and PM milking). During the monitoring period, the milk was collected every day, and after every two days in some instances. Performance monitoring was from April 2016 to March 2017.

The DXBMC operated with a total of four separate condensing units, and all used the same evaporator. The evaporator forms the underside of the inner tank of the DXBMC, and an insulation layer separated the internal tank and the outer tank. Table I below summarises the specifications of the system on the farm.

TABLE I: System description and specifications

Description	Specifications	Quantity
DXBMC	21 m^3, cylindrical, direct expansion, with horizontal agitators	1
Milking machine	Rotary type, 60 cows per cycle	1
Condensing units	Copeland Scroll compressors	4

Table II shows the sensors, meter, and logger used for the DAS (Data acquisition system) designed, built and installed at the dairy farm.

TABLE II: List of equipment used for the DAS

Equipment Description	Quantity
Landis and Gyr E650 power meter	1
HOBO ProV2 relative humidity and ambient temperature sensor	1
HOBO TMC6-HE temperature sensors	2
UX120-006M 4-channel analog data logger	2

The HOBO TMC6-HE temperature sensor was installed on the milk delivery pipe and inside the DXBMC's room. The sensors were connected to the UX120-006M 4-channel analog data logger configured to log at five-minute intervals. The Landis and Gyr E650 meter with an inbuilt logging capability captured the power consumption (active power, apparent power and reactive power) of the DXBMC at the same five-minute intervals during the cooling of milk from the initial temperature to the final required temperature of 4 **°C** (cooling cycle). A relative humidity and ambient temperature HOBO Pro V2 sensor with an inherent logging capability recorded the farm's ambient temperature and relative humidity. The volume of milk produced was obtained from the on-farm records. According to the raw milk standards, the milk's final temperature was assumed at a storage temperature of 4 **°C.** The schematic layout of the experiment and how the DAS was connected is shown in Figure 1.

Calculations and theory

The calculated electrical energy consumption (E_{cal}) for the entire duration of the cooling cycle was given by equation 5.1:

$$E_{cal} = P \; x \; t \tag{1}$$

Where:

P = power consumption of the DXBMC (kW)

t = time taken by the DXBMC to complete a cooling cycle (hours)

The total thermal energy removed from the milk during the cooling was given by equation 2

$$Q_m = \frac{mCp_m(T_{mi} - T_{mf})}{3600} \tag{2}$$

Where:

Q_m = thermal energy removed from the milk during cooling (kWh)

m = mass of milk cooled during a cooling cycle (kgs)

Cp_m = Specific heat capacity of milk (3.93kJ/kg.K)

T_{mi} = average initial temperature of milk (°C)

T_{mf} = average final temperature of milk (°C)

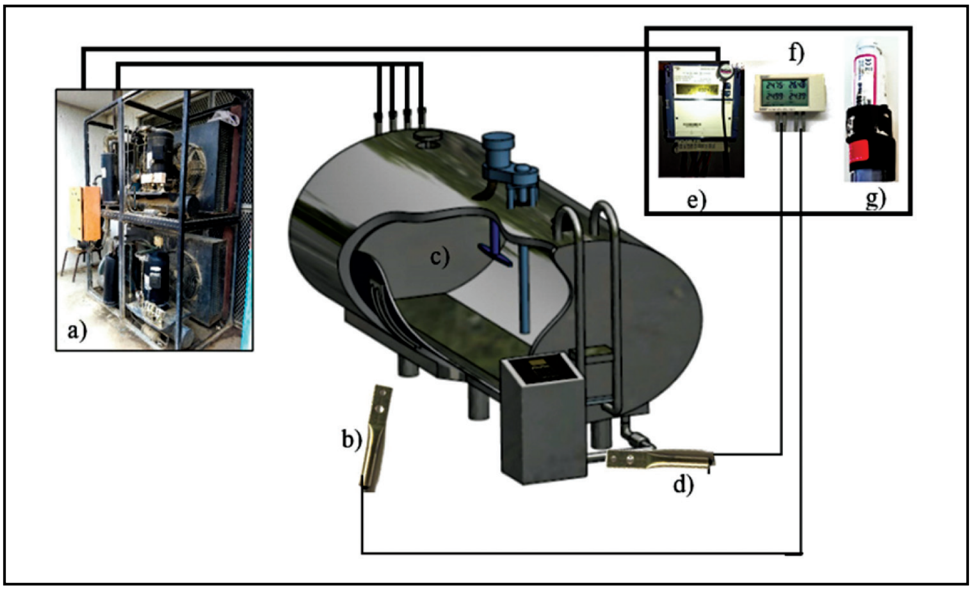

FIGURE 1: Schematic layout for the experiment

a) condensing unit, b) room-temperature sensor, c) bulk milk cooler, d) milk temperature sensor, e) power meter, f) four channel data logger, g) relative humidity and ambient temperature logger

The calculated COP (COP_{cal}) is the ratio of the thermal energy removed (Q_m) from the milk during the cooling process to the input electrical energy (E). The calculated COP was given by equation 3.

$$COP_{cal} = \frac{Q_m}{E} \tag{3}$$

Model formulation

This study used simple single output and multiple inputs multi-linear regression model (MLRM) with predictors being: the volume of milk, the temperature of milk, electrical energy, room temperature, ambient temperature and relative humidity. An MLR model is a mathematical equation which correlates the desired output to input parameters. It has a forcing constant and scaling constants of each of the input parameters and were determined by the ordinary least square method. MLR model is a simple form of an artificial neural network model. The MLR model's advantage is that it can easily predict each input parameter's variation with the desired output (Mhundwa and Simon, 2020). Variable selection was based on a correlation matrix for the predictors and the output. Equation 4 indicates the model.

$$COP_{mod} = \alpha + \beta E + \delta V_m + \varepsilon T_a RH + \lambda T_m \tag{4}$$

Where:

α = Forcing constant for COP model

β = Scaling constant for energy consumption (kWh)

δ = Scaling constant for the volume of milk (Ltrs)

ε = Scaling constant for the product of ambient temperature and relative humidity (°C %)

λ = Scaling constant for milk temperature (°C)

T_m – Temperature of the raw milk (°C)

T_a = Ambient temperature (°C)

RH = Relative humidity (%)

V_m = Volume of milk produced (Ltrs)

E = Energy consumption (kWh)

Predictor importance

The multi-linear regression model predictors were ranked by the importance of their weight contribution to the output (Millilan and Johnson, 1982; Robnik-Šikonja and Kononenko, 2003). The ranking of predictors was done using the ReliefF Algorithm in the Matlab Statistical toolbox (Palm, 2010) to differentiate the predictors' magnitude and importance concerning the COP for the DXBMC. The ReliefF algorithm determines to which predictors the COP is most sensitive.

Model testing and validation

The developed model fitness to the experimental data was evaluated using the determination coefficient (R^2). The model development and validation used 70% and 30% of the dataset, respectively. The mean square prediction error (MSPE), root mean square error (RMSE) and relative prediction error (RPE) formed the basis of evaluating the precision, accuracy and bias of the models as highlighted by Bibby and Toutenburg (1977) and Rook et al. (1990).

Results and discussion

Data was collected for the two distinct milking periods (that is the AM milking and the PM milking periods) for twelve months and were used to carry out the system's overall daily performance evaluation. Table III presents a summary of the data collected for this study

As can be observed from the table, the DXBMC's energy consumption varied between 68.50 kWh and 184.49 kWh. On average, the COP for DXBMC was 2.19. Notably, low milk volumes had low COPs for the DXBMC despite the low room temperatures recorded. Generally, the AM milking periods had high milk volume as well as higher COP values. Slight variation in the milk temperature was identified as influenced by the room temperature as the milk delivery pipelines were not insulated; however, no significant difference was observed. It can be observed that there was an increase in the COP with an increase in the milk volume, and suggests the improved performance of the DXBMC at high milk volumes. When analysed together, energy, the volume of milk, and milk temperature were significantly associated with the COP of the DXBMC at $P < 0.001$. The other variables, ambient temperature, relative humidity and room temperature, were not significantly associated with the COP. Henceforth, the volume of milk and energy formed part of the final model. However, since a refrigeration system's performance is affected by ambient conditions and due to the close association of ambient temperature and room temperature (Mhundwa et al., 2018), a product of ambient temperature and RH was also included in the model.

Using the 70:30 (model development and validation) criteria, the MLR model was developed to determine the effects of various predictors to the COP of the DXBMC.

TABLE III: Summary of the data collected for this study

	E (kWh)	V_m (Ltrs)	T_a (°C)	R.H. (%)	T_m (°C)	T_r (°C)	COP
Minimum	68.50	5,034.10	2.12	13.22	29.23	5.63	1.78
Average	110.84	7,371.16	17.58	68.35	33.19	19.26	2.19
Maximum	184.49	10,199	35.27	100	40.33	34.37	2.75

Table IV presents the coefficients of the scaling parameters. The scaling values predicted that electrical energy consumption of the DXBMC would increase if there were an increase in V_m delivered to the DXBMC, and T_m.

If there were an increase in E, T_a and T_r the COP of the system would decrease. An increase in RH and T_a led to a slight reduction in the COP even though this phenomenon could not occur simultaneously. It is worthwhile to mention that, T_a, and RH displayed low levels of significance in predicting the COP, as highlighted by the p values greater than 0.05 (Table IV). As observed in Table IV, the COP of the DXBMC reduced by 0.01796 for every kWh increase in energy consumption. With an increase in milk volume by a litre, the COP of the DXBMC would increase by 0.0003. Generally, the ambient conditions surrounding the DXBMC would likely reduce the COP for each degree Celsius increase in ambient temperature and room temperature. The p values for Energy, V_m and T_m are much smaller.

A 2D slice plot in Figure 3 presents each predictor's variation while the rest are kept constant. The plot visually deduces the overall effect of each predictor to the desired response (COP). Each predictor section's solid middle line indicates the change in the output based on the predictor variable if all other predictors remain constant. The slice plot also shows the 95% lower and upper confidence bounds (dashed curves) for the predicted COP. We can deduce from this plot that an increase in energy consumption by a unit kWh will likely lead to a reduced COP by 0.9 %, while an increase of milk volume by one litre will increase the COP by 0.0134 %. It is worth noting this; the increase of other predictors did not show much change in the COP. Figure 2 illustrates the calculated COP and modelled COP.

As shown in Figure 3, the modelled COP closely mimic the calculated COP with an adjusted $R^2 = 0.957$. This indicates that 95.7% of the data's variation is explained by the MLR model using the predictors. This suggests a strong relationship between the predictors and the targeted COP at 95% confidence level. The difference between the means of COPcal and COPmod were statistically insignificant with a p value = 0.992. Furthermore, the developed model is statistically significant as was deduced by significance p = 1.31×10^{-120}. The model can predict the COP with relatively high precision as indicated by a low RMSE = 0.0406 with a standard error for using the model to predict the COP of 0.0392, thus implying the experimental data produces a good fit. Figure 4 shows the residual plot for the modelled COP.

The residual plot shows no distinct pattern of the residuals indicating the residuals' randomness, with most of them being close to the zero residual. Figure 5 illustrates the effects of each predictor on the COP of the DXBMC.

Based on Figure 5, this plot shows that energy consumption by the DXBMC has a negative effect on the performance of the DXBMC. An increase in energy consumption by 62.85% (68.503 kWh to 184.49 kWh) will reduce the COP of the DXBMC by 2.08. On the other hand, the increase of the milk volume by 50.64% (5 034 to 10 199) will likely increase the COP of the system by 1.496. Also, an increase in the milk temperature by 27.52% (29.23 °C to 40.33 °C) would also increase the COP of the DXBMC by 0.78. Ambient temperature and relative humidity had an insignificant effect on the COP of the system. The effects of the environment on the DXBMC's COP is attributed to its location at the farm. In this case, the DXBMC was housed

Table IV: Input parameters and scaling coefficients for the COP of the DXBMC

Predictor	Symbol	Scaling Notation	Scaling Constant	P-value	Output
Energy	E	β	-0.01796	2.71×10^{-99}	
Volume of milk	V_m	δ	0.0003	1.16×10^{-112}	
Ambient Temperature and Relative Humidity	T_aRH	ε	-3.39×10^{-6}	0.714	COP
Milk Temperature	T_m	λ	0.064	8.82×10^{-49}	
Constant		α	-0.0165	0.867	

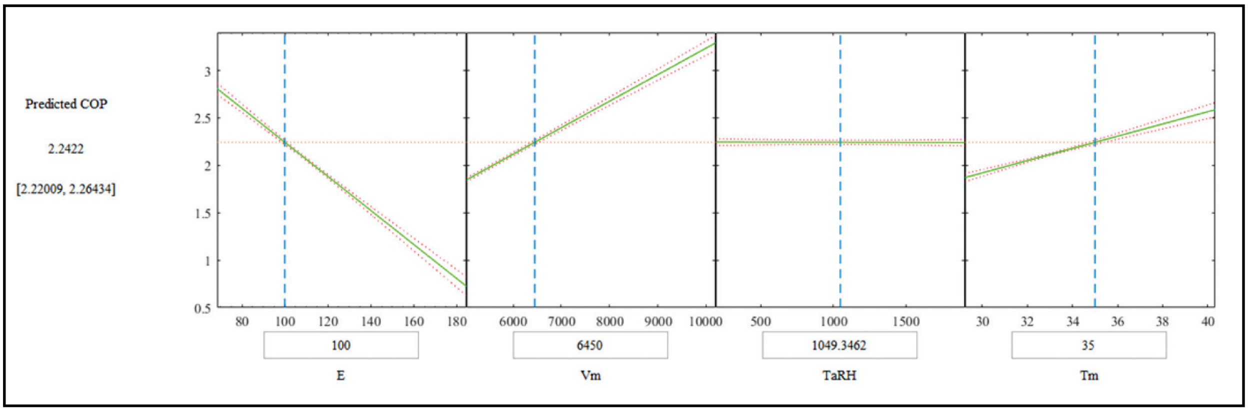

FIGURE 2: 2D slice plot of predictors and COP for the on-farm DXBMC

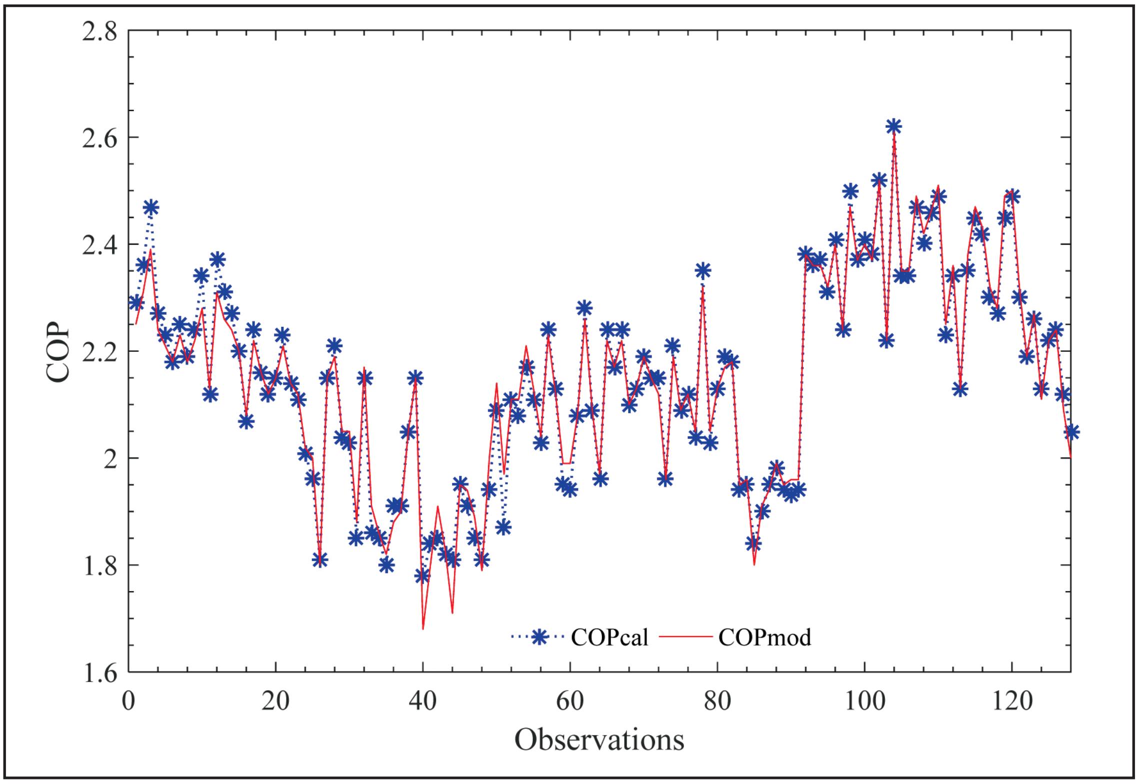

FIGURE 3: Calculated COP and modelled COP for an on-farm DXBMC

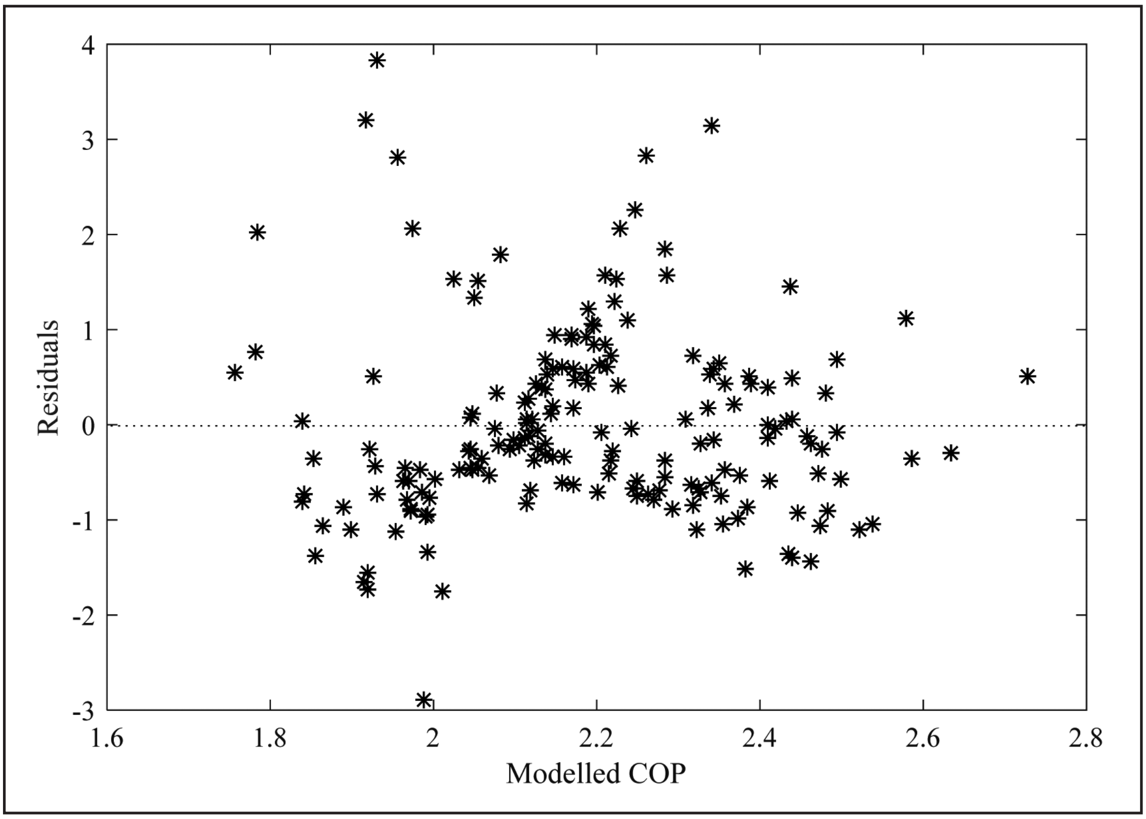

FIGURE 4: Residual and Modelled COP for the on-farm DXBMC

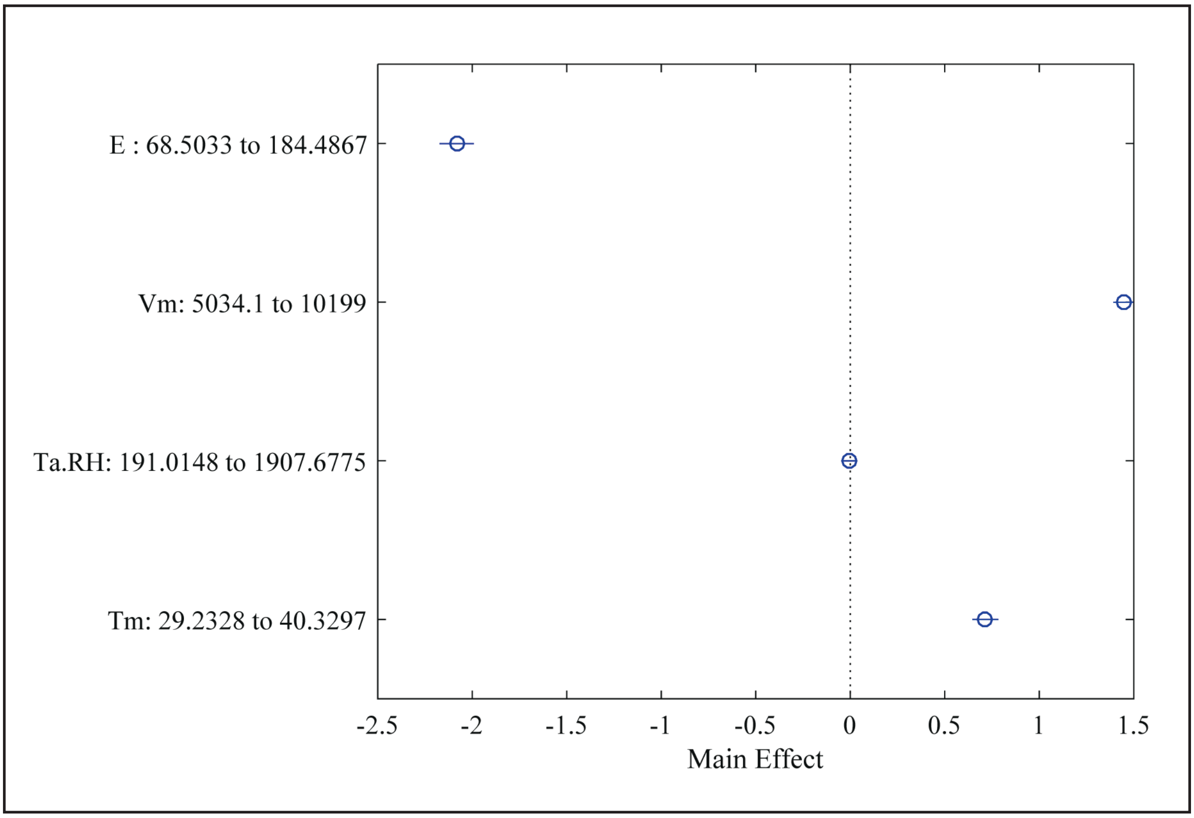

FIGURE 5: Effects of each predictor to the COP of the on-farm DXBMC

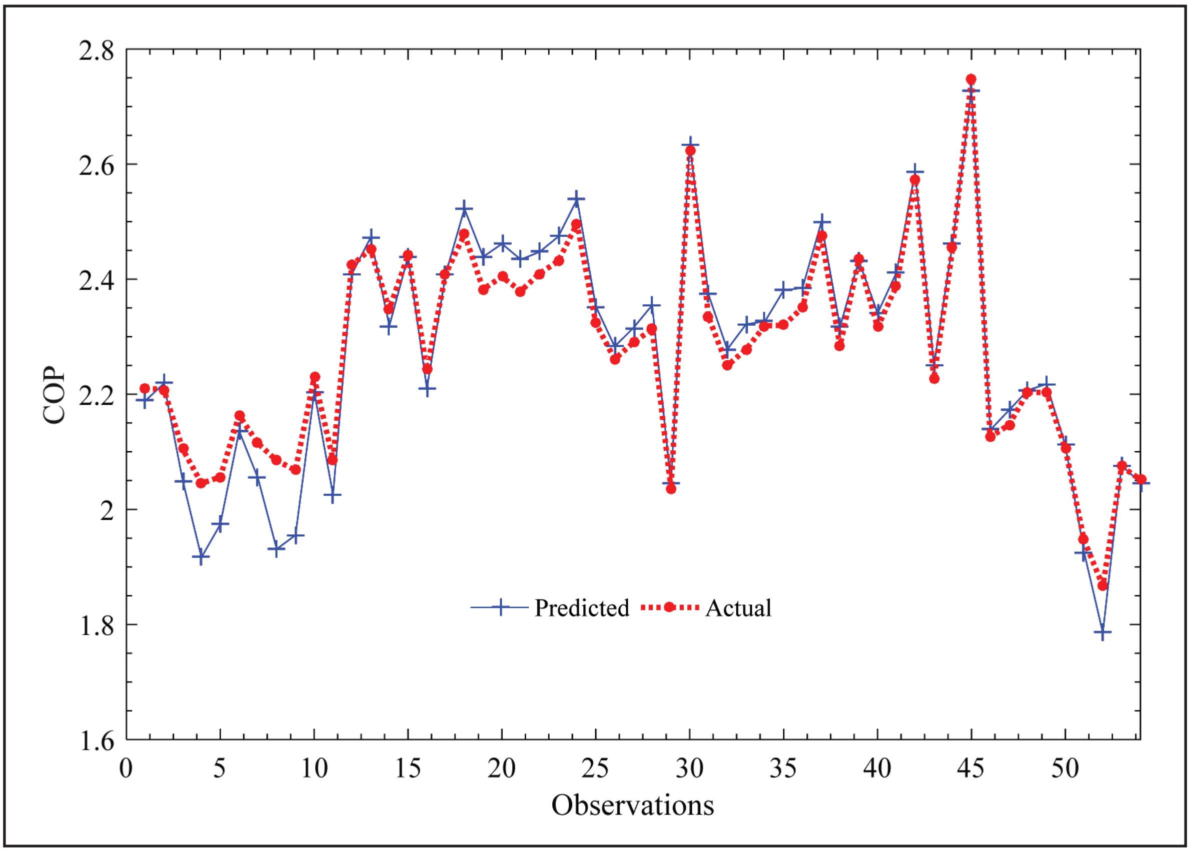

FIGURE 6: Comparison of the actual COP and predicted COP.

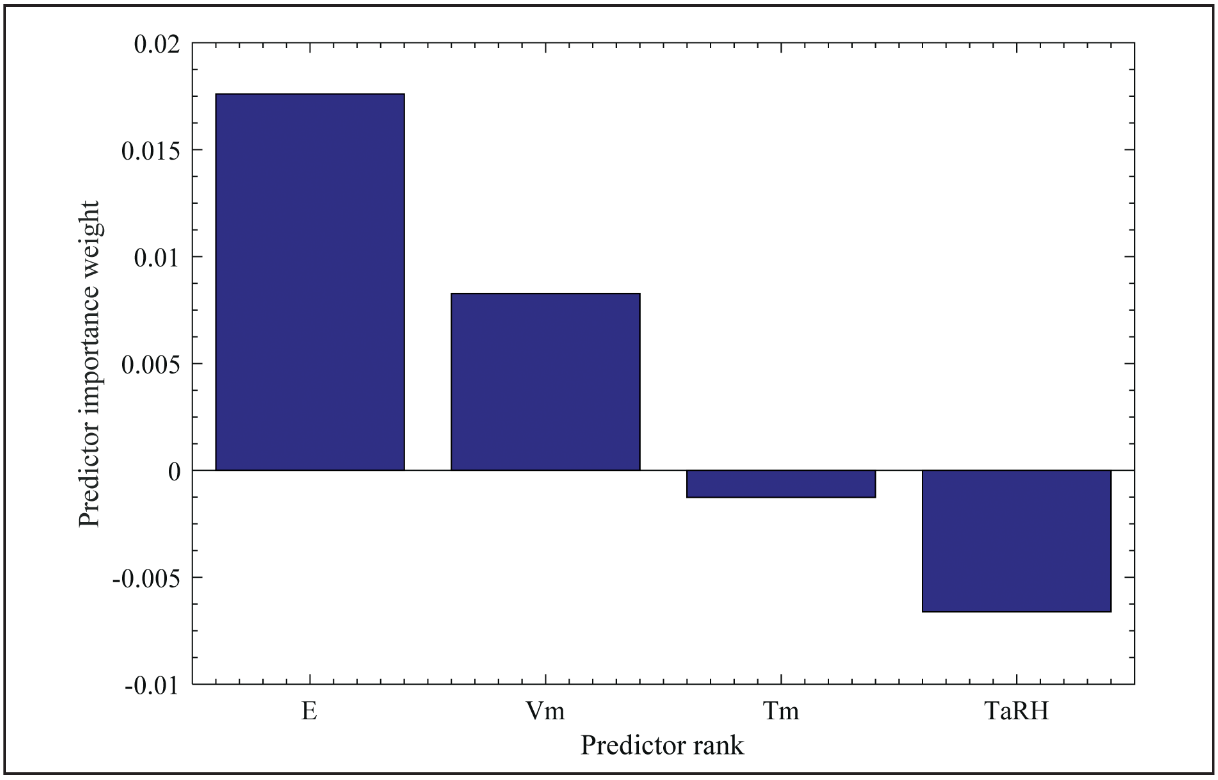

FIGURE 7: Predictor ranking according to importance

such that there is minimal interaction with the external conditions.

Model validation

Model validation was done using 30% of the data obtained from the same DAS and the similar techniques used for the analysis. The model was used for forecasting with the appropriate predictors presented in the preceding section. The predictions of the model developed were subsequently compared to the calculated COP of the DXBMC. The RPE was used to evaluate the developed model's suitability as proposed by Fuentes-Pila et al. (1996). In this light, the model had RPE and RMSE of 2.735 % and 0.082, respectively. This suggests that the MLR model indicates an acceptable prediction precision since the RPE values ranged from 10% to 20% (Fuentes-Pila et al., 1996). Figure 6 illustrates the comparison of the Actual COP and those predicted by the MLR.

As shown in Figure 6, the predicted COP closely mimic the actual COP with R^2 value of 0.956. The high R^2 value suggests that the developed model could be used on similar direct expansion DXBMC systems to predict the COP.

Ranking of predictors by weight of importance

The ReliefF Algorithm in the Matlab Statistical toolbox was used to rank predictors (Palm, 2010; Mhundwa et al., 2017). The algorithm differentiates through the computation of ranks and weights of the predictors, the magnitude and direction between primary and secondary contributors to the desired output is a critical parameter that it uses. The primary contributors will have a positive magnitude while the secondary will have a negative magnitude and ranging from -1 to 1 with large positive weights assigned to essential attributes, as indicated in Figure 7.

It can be deduced that energy, and volume of milk were primary contributors to the COP while milk temperature and the product of ambient temperature and RH were secondary contributors.

Conclusion

An on-farm DXBMC was monitored during April 2016 – March 2017 and its COP was evaluated using MLR modelling technique. Based on our analysis, the noticeable findings from this study are as follows:

i. The COP of an on-farm DXBMC can be predicted with high accuracy using an MLR model with energy, the volume of milk, the temperature of milk, relative humidity and ambient temperature.

ii. Energy consumption had the most significant influence on the COP of the DXBMC followed by the volume of milk, the temperature of milk and relative humidity and ambient temperature in that order.

iii. Energy consumption and the volume of milk are primary contributors to the COP while milk temperature and the product of ambient temperature and relative humidity were secondary, due to the location of the DXBMC.

Acknowledgments

We are grateful to acknowledge the financial support from the University of Fort Hare.

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