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ARTIFICIAL NEURAL NETWORK MODEL FOR WATER CONSUMPTION PREDICTION IN DAIRY FARMS

Márcia Regina OSAKI[1], Julio Cesar Pascale PALHARES[2], Fernando Guimarães AGUIAR[3]

[1] Universidade Virtual do Estado de São Paulo, São Paulo, São Paulo, Brazil.
[2] Embrapa Pecuária Sudeste, São Carlos, São Paulo, Brazil.
[3] Universidade Federal de São Carlos, São Carlos, São Paulo, Brazil.

Corresponding author:
Márcia Regina Osaki
marciaosaki@alumni.usp.br

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Abstract
This work presents a model based on artificial neural network (ANN) applied to predict water consumption in Brazilian dairy farms. Inputs were simple process data such as number of lactating cows, milk productivity, type of management, among others, with low computational cost and satisfactory data prediction. Data used for ANN training was acquired during two years from 31 farms in semi-confined dairy production. The analysis of the results was based on the following statistical models' indicators: R^2 (Coefficient of determination), BIAS (trend coefficient), MAE (mean absolute error), RMSE (Root-mean-square deviation), NRMSE (percentage of the mean of the observations) and RAE (Relative absolute error). After performing the ANN training, the results showed good accuracy to predict water consumption in Brazilian dairy farms, with an average absolute error of 28.4% being obtained. On the other hand, considering the dataset used for ANN validation, an average absolute error of 48% was obtained.

Keywords: Lactating Cows. Semi-confined. Water Efficiency. Water Meter.

1. Introduction

Dairy is expected to be the fastest expanding livestock sector until 2030, with global milk production projected to increase by 22% (OEDC-FAO 2021). Dairy farms rely on water as an essential input for milk production, and the considerable amount being used has triggered the dairy sector at global and national levels (DFC 2016; FAO 2016; IDF 2016). In a global perspective, dairy farms use 18.1% of the total consumptive water (Heinke et al. 2020). The Brazilian National Water Agency (ANA 2019) estimated dairy production plays an important role providing 37.3% of human-edible proteins but the risk of economic losses in livestock production due to water shortage could be about $44.57 billion Brazilian currency by 2035. In 2019, Brazilian livestock production demanded 11.6% of all water consumed in the country (ANA 2020). According Shine et al. (2020) it is clear that the global production of milk and dairy must be carried out with considerations regarding water consumption. Thus, research in this domain will become increasingly important and researchers aim to identify new methods to improve the water use of dairy farming.

The water management in the dairy systems start from the knowledge of the water consumption on the different activities in the farm. However, this knowledge is not yet common in the farm reality due to the non-use of consumption measurement systems. According to Williams et al. (2017), the consumption of water by cattle is not well understood by farmers and scientists. Shine et al. (2018b) point that there has been little or no work to date to indicate the overall and direct uses of water including drinking, parlor and other in dairy farms.

Palhares et al. (2021) emphasize that the phrase is true: it is not possible to manage what we do not know. To promote water management in beef cattle systems, the first step is to know how the resource is used and in what volume. Palhares et al. (2020) provides a detailed understanding of livestock water uses and their respective efficiency, so it can help the internalization of water management by the sector. Palhares and Pezzopane (2015) emphasizes that professionals should promote animal systems that improve water efficiency. In this way, production systems will improve resilience and adaptability. Franco et al. (2021) highlights that the cattle industry should seek ways to accurately account for water usage and minimize water utilization in livestock systems. Robinson et al. (2016) points that water is one of the most important factors on a dairy farm because it is essential for cow consumption to support milk production. This dependence may lead to more active regulation and monitoring of water use. Shine et al. (2018c) evaluate that water metering can be expensive, requiring several meters to be installed and maintained on each farm. Shine et al. (2020) think that researchers should consider analyzing a small number of farms using accurate data (collected using metering equipment) in order to develop a model which can in turn be used to predict on-farm direct dairy water consumption.

Considering different machine learning models, artificial neural networks (ANN) stand out Haykin (2007), in which they have a natural propensity to store experimental knowledge and make it available for use. It resembles the brain in the aspect that knowledge is acquired by the network from its environment through a learning process and by the connection between neurons known as synaptic weights, used to store the acquired knowledge. In the learning process, an algorithm is used, which has the function of modifying the synaptic weights of the network in an orderly way to reach a desired design objective. Modifying synaptic weights is the traditional method for designing neural networks. Neural networks allow modeling systems from experimental data, or even a combination of known physical laws and obtained experimental data. They also provide non-linear representations that result in better models more suited to the real system, ensuring higher quality results.

The bibliographical survey on the use of water in livestock showed that models with the use of neural networks have already been developed. According Shine et al. (2018a), empirical prediction models developed from farm dairy data to evaluate water consumption may provide: (1) key decision support information to both dairy farmers and policy makers. (2) a tool for conducting macro scale environmental analysis (3) a means of calculating the impact of dairy farming on natural resources, (4) a method of benchmarking and improving water efficiency (5) an aid for developing regulations.

In Ireland, four mathematical models: CART decision tree (CDT), Random Forest (RF), Artificial Neural Network (ANN) and Support Vector Machine Regression (SVR) were analyzed for predicting water and electricity consumption in dairy farms, using inputs from 58 farms to forecast 15 variables for electricity and 20 for water. The objective of the work was to find the best combinations of variables previously selected, to save computational resources. The variables used were number of dairy cows, milk production, frequency of hot washing, automatic parlour washing, time spent on parlour washing daily and a few more. The models envisioned the potential increase of up to 50% in milk production by 2020, compared to 2007-09, with the concern of sustainable consumption of electricity and water. They were looking for an accurate forecast of water and electricity consumption to provide decision-making information with economic data. For water, the best algorithm was the RF, with a concordance correlation coefficient (CCC) 0.76 and an error of 38.3%.

An artificial neural network for milk yield prediction was built by Zhang et al. (2016). A system was created to optimize milk production forecasting in Ireland, called Milk Production Forecast Optimization System (MPFOS) using the Adaptive Stratified Sampling Approach (ASSA) to filter and sort the input data and ensure the training dataset. As input were chosen: 1) daily milking yield for each cow, 2) specific record of the cow, such as date of calving and number of lactations and 3) climate data, such as air temperature, wind speed, sunshine and soil temperature. Data from 2004 to 2008 were trained by the algorithm and then validated with data from 2009. MPFOS selected the most effective of the nine prediction models. The Root Mean Square Error (RMSE) value varied substantially (from 68.5 kg of milk production to 210.4 kg per day).

A Brazilian study, da Rosa Righi et al. (2020) evaluated milk production considering animal feeding. The work proposed a computational model using the *Internet of Things (IoT)* to automate and individualize animal feeding and its impact on milk production. The results were quite assertive and it was also possible to predict nutritional problems to enable feeding plans for the cows. The modeling was done with the ARIMA (Auto-Regressive Moving Average model), which is a model used to forecast demand. In parallel, Neural Network and Random Forest models were tested, which differed on performance and speed. The application of the model had a prediction accuracy of 94.3%, related to the application of the EMA (exponential moving average).

In this context, the objective of this work was to develop an artificial intelligence model, based on ANN, with low computational cost and satisfactory data prediction, capable of predicting water consumption based on simple variables: number of lactating cows, milk productivity and type of management, among others. The development of the model in this work differs from others both in the input variables and in the statistical methods previously applied, as we will describe below.

2. Material and Methods

Data Set

At the beginning of 2019, Embrapa Pecuaria Sudeste had started the program *Water Management in Dairy Farms in Brazil* in partnership with the private sector. The first step of the project was inviting dairy farmers to install water meters to measure four different water consumptions (parlor washing, corral washing and animal drinking).

With the acceptance by each farmer, the autonomous water meters to record direct water volumes (m^3) were installed under the guidance of a technician in one or more points of water consumption of each farm. The reading of the water meters was performed monthly by the farmer or by the farmer together with the technician from agroindustry and these data were stored in a spreadsheet file, sent by email to Embrapa Southeast Livestock.

In total, 31 commercial dairy farms had their water consumption monitored throughout the period Jan 2019 – Dec 2020. The variables total milk produced and number of lactating cows per month were also monitored. Two indicators were calculated: liter of water per milk produced and liter of water per lactating cow.

Other information gathered was if the farmer had scrapped off manure before washing or just cleaned parlor and corral washing, they with water under pressure. Farmers were also encouraged to note any events that influenced water consumption as occurrence of leaks, change of water meter, etc.

Artificial Neural Network Approaches and Implementation

Generally, the artificial neuron is a logical mathematical structure that aims to simulate the form, behavior and functions of a biological neuron (Guyon 1991). Thus, dendrites are replaced by inputs whose connections to the cell body are made through artificial elements called weight (simulating neuronal synapses). Stimuli are received and processed by the sum and bias function. The threshold for triggering the biological neuron suggests an analogy with the transfer function in artificial neurons. (Guyon 1991; Chua and Yang 1988). Figure 1 shows a representation of the artificial neuron.

Research in neural networks was started in 1943 (Piccinini 2004). It was a pioneer study about the behavior of biological neurons in order to create the corresponding mathematical model for the interpretation of the functioning of the neuron as a binary circuit (Mcculloch and Pitts 1943).

It' is important to highlight that the research in neural networks reached a peak in the 1980's, developing the backpropagation training algorithm (BPTA) which provided training for multilayer Perceptron networks (Rumelhart and Hintont 2019). As a result, networks with high generalization power, allowing implementation of different applications were developed.

In BPTA a training set is presented to the neural network with input and output pairs. The input matrix is propagated layer by layer to the output layer. The network output matrix is then compared to the desired output matrix and the difference between the two outputs (calculated and desired) is the network output error. This error is propagated back to the network to adjust bias and weights to the next iteration (generation) output error be reduced. This process is repeated for all pairs of the network training set, until the output error is acceptable (Rumelhart and Hintont 2019; Shen et al. 2022).

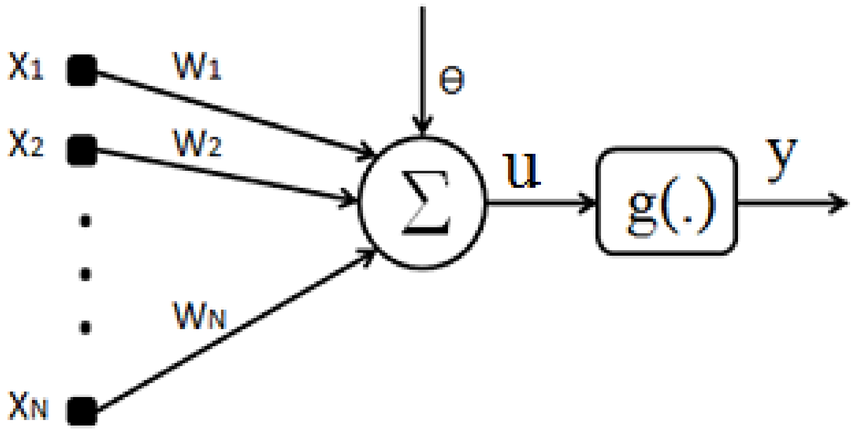

Figure 1. Artificial neuron model, considering N input values ($X_1 \dots X_N$), weights ($W_1 \dots W_N$), threshold (θ), transfer function (g(.)) and output value (y).

Figure 2 shows the topology of the MLP implemented in this work, with four hidden neural layers with 40, 30, 20 and 20 neurons, respectively, and one neuron in the output layer. The hidden layer activation functions were sigmoid tangent while linear identity function was used to the output layer.

Considering the ANN model implemented, 7 different variables were used as input: annual average milk production, annual average lactation cows, annual average milk production per cow, water consumption by specific usage, if the farmer scrapes the waste after milking (No=0, Yes=1), if the farmer washes the milking parlor with water under pressure (No=0, Yes=1), and the type of production system.

To validate the generalizability of the trained neural network, a validation set of 6 farms was used (a total of 12 experimental data set, of which 6 referred to 2019 and another 6 to 2020) and then applied the k-fols cross-validation method.

To adapt the different values and homogenize the input data for the activation functions of the hidden layer neurons (sigmoid tangent), the data normalization methodology of the six different inputs of the neural network was used, so that all variables were in the range [0 to 1]. Additionally, numerical conversions were used.

Metrics for model validation

The following metrics were used for regression, where n is the number of observations, A_i is the value of the i^{th} observation in the validation dataset, $\bar{A}$ is the average value of the validation dataset and A and P_i are the predicted value for the i^{th} observation.

Coefficient of determination: R^2

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (A_i - P_i)^2}{\sum_{i=1}^{n} (A_i - \bar{A})^2}$$

The closer R^2 is to 1, the better the prediction. However, it is necessary to be careful when calculating this determination coefficient because it may lead to erroneous conclusions. In fact, some points of influence can particularly increase the value of the coefficient of determination, which can sometimes suggest that the predictions are quite accurate (ASPEXIT 2022; Saber et al. 2022).

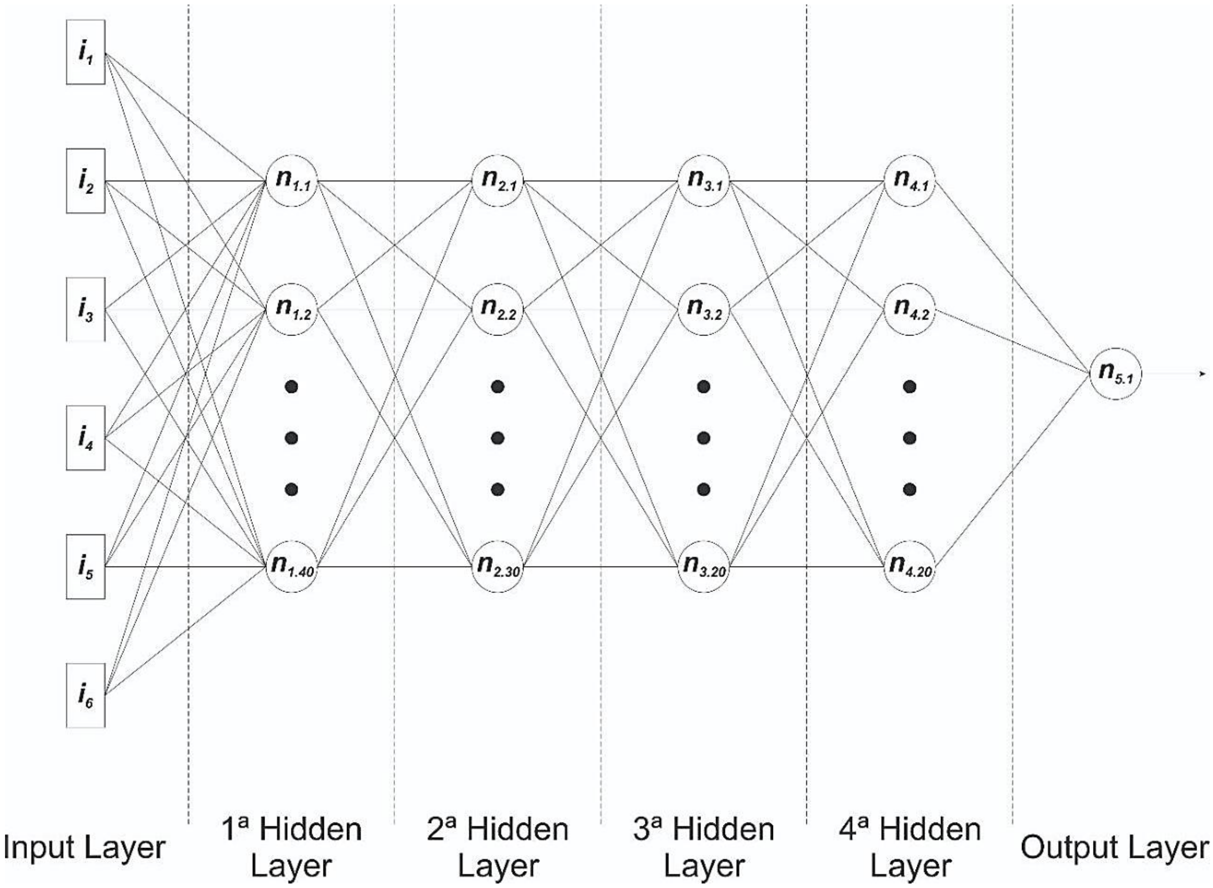

Figure 2. Implemented artificial neural network with four hidden layer.

The trend coefficient: BIAS

$$\text{BIAS}=\frac{\sum_{i=1}^{n}(P_i\text{-}A_i)}{n}$$

The BIAS trend coefficient allows assessing whether the forecasts are accurate and whether the model tends to over or underestimate the values of the variable of interest. The smaller BIAS (closer to 0), the better is the prediction. This indicator does not account for the variability of predictions. Indeed, if the predicted values are at the same time over and underestimated, the BIAS can still be relatively low. (ASPEXIT 2022).

The mean absolute error: MAE

$$\text{MAE}=\frac{\sum_{i=1}^{n}|P_i\text{-}A_i|}{n}$$

The only difference between the MAE and the BIAS is the absolute value of the differences between the real and the predicted values. One strong advantage of the MAE is that it gives a better idea of the prediction accuracy. However, it is not possible to know if the model tends to over or underestimate the predictions. (ASPEXIT 2022; Saber et al. 2022)

Root-mean-square deviation: RMSE

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(P_i\text{-}A_i)^2}{n}}$$

The RMSE provides an indication regarding the dispersion or the variability or the prediction accuracy. It can be related to the variance of the model, but often the RMSE value is difficult to interpret because it cannot tell whether a variance value is low or high. To overcome this issue, it is more interesting to normalize the RMSE so that this indicator can be expressed as a percentage of the mean of the observations (NRMSE). This makes the RMSE more relative to what is being studied. For instance, a RMSE of 10 is relatively low if the average of observations is 500. However, the model has a high variance if it generates an RMSE of 10 for an average observation of 15. In fact, in the first case, the variance of the model reaches only 5% of the mean while it reaches more than 65% of the mean in the second case. (Willmott and Matsuura 2005; ASPEXIT 2022; Saber et al. 2022)

Relative absolute error: RAE

$$\mathrm{RAE}=\frac{\sum_{i=1}^{n}|A_i-P_i|}{\sum_{i=1}^{n}|A_i-\bar{A}|}$$

Relative Absolute Error (RAE) is a way to measure the performance of a predictive model. RAE is not to be confused with relative error, which is a general measure of precision or accuracy for instruments like clocks, rulers, or scales. It is expressed as a ratio, comparing a mean error (residual) to errors produced by a trivial or naive model. A good forecasting model will produce a ratio close to zero. A poor model (one that’s worse than the naive model) will produce a ratio greater than one.

3. Results

Table 1 shows the descriptive data about productive aspects and water consumption by year of the study. Average daily milk production in 2020 was 9.7% higher than in 2019 and average daily water consumption was 2% lower. There was a 2.8% increase in the number of lactating cows in the period. The average milk production was 19.7 and 20.5 liters per cow in 2019 and 2020, respectively, substantially higher than the Brazilian average milk production of 7.2 liters per cow (IBGE 2020). In both years, the percentage of farmers who scraped the milking parlor before washing was 74%. In 2019, farmers who washed the milking parlor with water under pressure represented 65% and increased to 71% in 2020.

Table 1. Summary of average productive aspects by year monitored.

Milk Production					
Year	Average (L day-1)	SD	CV (%)	Max. (L day-1)	Min. (L day-1)
2019	1.303	672	52	2.905	482
2020	1.424	702	49	3.065	324
Lactating Cows					
Year	Average (L day-1)	SD	CV (%)	Max. (L day-1)	Min. (L day-1)
2019	70	27	39	122	27
2020	72	28	41	126	28
Water Consumption					
Year	Average (L day-1)	SD	CV (%)	Max. (L day-1)	Min. (L day-1)
2019	7,170	7.937	111	33.007	352
2020	6,972	7.318	105	30.508	471

*SD- standard deviation / CV- coefficient of variation /Max. – Maximum / Min. – Minimum.

4. Discussion

High dispersions are expected in studies that involve data from commercial farms because these farms represent different production systems, environmental conditions, nutritional managements, quality of worker, etc. The indicators milk production and number of lactating cows are still influenced by the dry and rainy season. Because of it the variation of coefficients for these two indicators was significant for both years (Table 1). On the other hand, the dispersion of the average water consumption per day among the farms was much more accentuated. In addition to all the productive and environmental aspects mentioned above influencing water consumption, the water meters installed on the farms measured different uses. This justifies the high variability of the coefficient to this indicator. Both Shine et al. (2018c) and Higham et al. (2016) show that milk production had the largest impact on water consumption. The first also observed a moderate correlation between dairy cow numbers and water consumption. Shine et al. (2018a) detected that machine-learning prediction accuracy for water consumption in dairy farms was impacted because over 60% of farms manually reporting water consumption on a monthly basis, which did not facilitate adjustments for leakage to be made and variability's in cow drinking water due to varying milk production levels. Shine et al. (2018b) verified that relationship strengths decreased between water consumption, number of lactating cows and milk production. Authors suggests a lesser effect of milk production and stock and increased effect of managerial processes, environmental conditions and farm infrastructure on water consumption.

There is a direct relationship between the number of lactating cows, milk production and water consumption. As the first two require water consumption, there should be an increase in water usage, unless there is a gain in water use efficiency.

Results indicate a gain in water efficiency from 2019 to 2020. Carra et al. (2021) state that efficiency gains in the use of water destined to livestock are achieved from the implementation of best water practices that involve indirect and direct uses of water. In this study, there was no follow-up of the farms regarding the implementation of best water practices. In terms of rational use of the natural resource, the aim is to reduce water consumption, maintaining or increasing the production of the product. This was verified among the farms in the period.

The gains of water efficiency in the period are corroborated when we verified that the average indicator liters of water lactating cow^{-1} day^{-1} was 107 L day^{-1} in 2019 and 101 L day^{-1} in 2020. For the indicator liters of water liter of milk^{-1} day^{-1}, the average in 2019 was 5.6 L day^{-1} and in 2021 5.2 L day^{-1}. The efficiency gain represented an avoided consumption of water of 6 L day^{-1} per lactating cow and 0.4 L day^{-1} per liter of milk.

Figure 3 presents the results obtained with the simplified water consumption prediction model when the ANN is trained and verified with the same set of data. There is good accuracy, with an average absolute error of 28.4%. On the other hand, considering just the dataset used for ANN validation, an average absolute error of 48% was obtained and the results are shown in Figure 4.

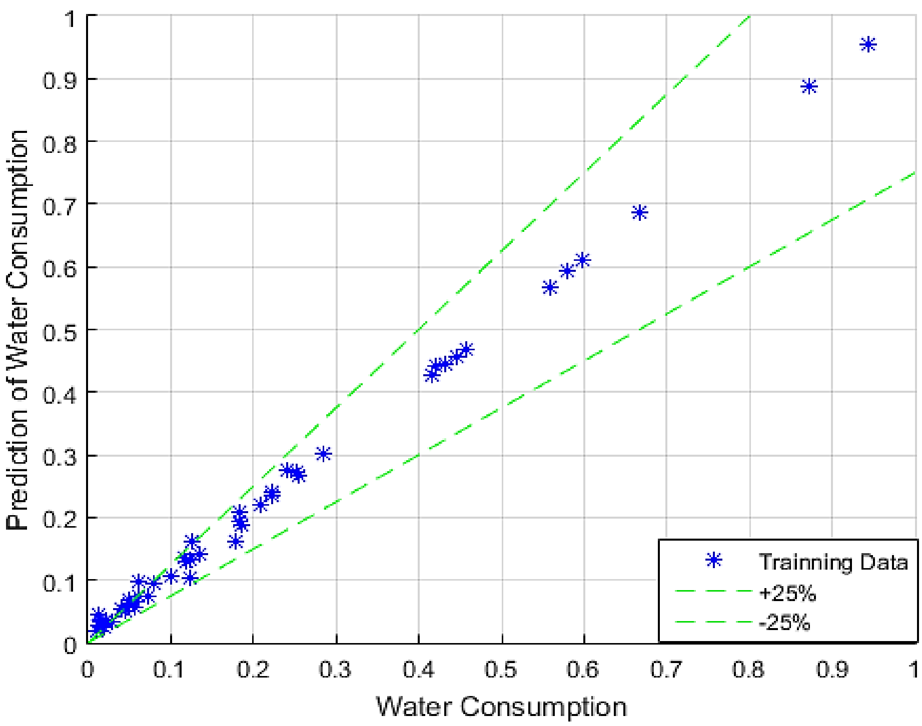

Figure 3. Water consumption prediction model for dataset used in ANN training.

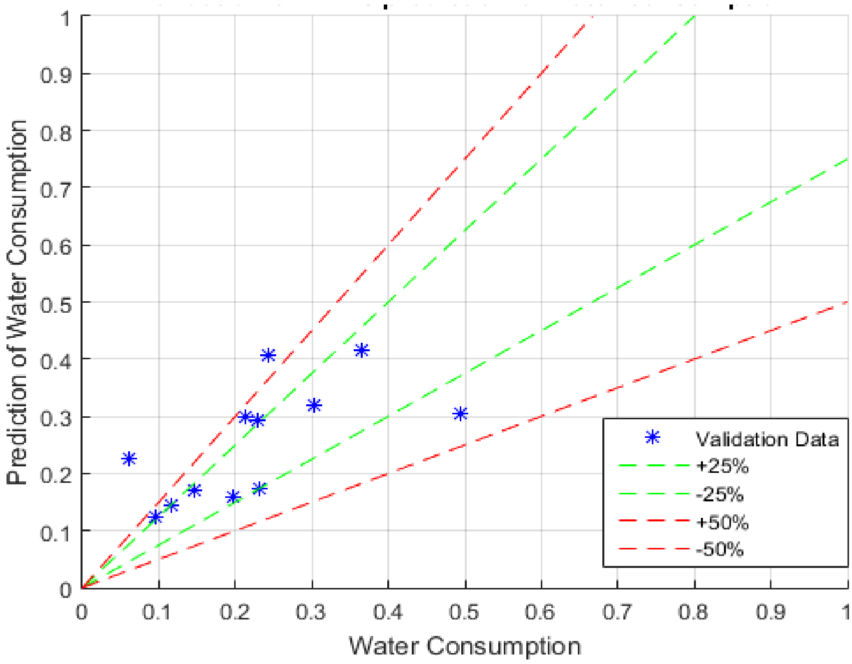

Figure 4. Water consumption prediction model for dataset used in ANN validation.

To analyze the results, this research utilizes both regression and classification algorithms which evaluate the yielded results differently.

Model assessment and analysis methods

Coefficient of determination: R^2

$$R^2=1-\frac{\sum_{i=1}^{n}(A_i-P_i)^2}{\sum_{i=1}^{n}(A_i-\bar{A})^2} = 0.338$$

This value is far from R^2 of 1(one) and does not suggest enough accuracy of the predictive model.

The trend coefficient: BIAS

$$BIAS=\frac{\sum_{i=1}^{n}(P_i-A_i)}{n}=0.0284$$

To visually assess whether the predicted values are under or overestimated, it is possible to use Figure 4 that shows data scattered above and below the average line, so this is not a biased predictive model.

The mean absolute error: MAE

$$MAE=\frac{\sum_{i=1}^{n}|P_i-A_i|}{n} = 0.0738$$

The MAE is close to zero, it gives an idea of accuracy of the predictive model.

Root-mean-square deviation: RMSE

For the case of this work:

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(P_i-A_i)^2}{n}} = 0.0944$$

And normalizing by the average of A:

$$NRMSE=\frac{RMSE}{\bar{A}}=0.4197$$

NRMSE is high, indicating big dispersion of prediction.

Relative absolute error: RAE

$$RAE=\frac{\sum_{i=1}^{n}|A_i-P_i|}{\sum_{i=1}^{n}|A_i-\bar{A}|}=0.8550$$

The RAE is closer to the trivial or naïve model than to a good model. The predictive model is no worse than the naïve model, but it's not a great model as well.

The assessment indicators R^2, BIAS, MAE, RMSE (NRMSE) and RAE are respectively 0.338, 0.0284, 0.0738, 0.0944 (0.4197) and 0.8550.

None of these mentioned indices is considered better than the others. On the contrary, all metrics should be used together to provide a better understanding of prediction accuracy.

Precision and accuracy are two ways of thinking about error. Accuracy refers to how close a measurement is to the true or accepted value. Precision refers to how close measurements of the same item are to each other. Precision is independent of accuracy. This means that it is possible to be very precise but not very exact, and it is also possible to be exact without being precise. The best quality scientific observations are accurate and precise.

As expected, a higher average absolute error was obtained in the data used for ANN validation when compared to the average absolute error in the data for ANN training. Even so, this model presents itself as a promising tool as it makes use of input data that are easy to obtain, even on farms with low-tech processes.

5. Conclusions

This work presented a model of artificial neural network to predict water consumption in dairy farms, starting from simple process data as input. Although it is not a computationally sophisticated model, it was able to predict water consumption on unknown farms (validation dataset). Even with the limitations on the input variables, it was possible to obtain some prediction, although not totally accurate. Considering that the reality of farms in developing countries - with their typically poor water usage monitoring - should be changed, this simplified model may be seen as a starting point in a future more comprehensive analysis of water consumption efficiency in the activity that the farmer didn't have scrapped off manure before washing.

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Ethics Approval: Not applicable.

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