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PRIMARY RESEARCH

Neural networks application for water distribution demand-driven decision support system

Cherl Nino M. Locsin [1*], Rosana J. Ferolin [2]

[1, 2] University of San Carlos, Cebu, Philippines

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Abstract

Water is a basic necessity in our daily activities. Therefore, there should be enough supply of water to meet our demands. On average, in Cebu City, the Philippines alone, 24 cubic meters per household per month is used [1]. To meet the demand, water has to be properly distributed considering several factors, which are: (1) temperature, (2) precipitation, (3) population, (4) water rates, (5) historical water use, (6) water supply, and (7) socioeconomic profile. This study developed an Artificial Neural Network (ANN) water distribution decision support system that predicted water demand. The ANN was trained using historical records of the factors mentioned above and provided municipal and barangay water demand predictions with accuracy above 90%.

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I. INTRODUCTION

In Metro Cebu, only 43% of the total water demand is currently covered by the Metropolitan Cebu Water District (MCWD). Metro Cebu covers a total of 1,062.88 km44^2 of land from Danao City to Carcar City, with a total population of 2,849,213 people [1, 2, 3]. However, MCWD only covers the distribution from Compostela to Talisay [2].

An early study, conducted in 1998, indicated that the water resource management of MCWD in Metro Cebu was critical. MCWD was serving only 23% of the total households, and a small fraction of both industrial and commercial establishments [2]. Since then, the service coverage of MCWD is yet to reach half of the total demand, increasing only by 20%, to a total of 43% in 2016 [3].

Attributed to the water demand in Metro Cebu is its rapidly growing economy, proven by its Gross Domestic Product (GDP) growth of 7.5% in 2017 from its previous GDP growth of 7% in 2016 [4]. As a result of the rapid economic growth, more infrastructures are being built as Cebu becomes a prime location for industrialization, causing an arising water demand [5, 6]. Aside from the arising water demand due to industrialization, water use in Metro Cebu is already high. This amounts to 24 cubic meters per capita (measured by per household) per month, which is above the global per capita use of 18.9 cubic meters per month [5, 7, 8].

Currently, MCWD is striving to increase its service coverage from 43% to 66% in 2020 [3]. Therefore, the water demand in the upcoming years has to be considered. To do so, the six (6) factors affecting water demand have to be utilized.

ANN have been used in predictions, in which some of its applications are to predict water demand [9, 10, 11], wind speed [11], and maize crop yield [12].

An ANN is a network of interconnected neurons that is capable of learning [13, 14, 15]. In developing an ANN, there are six (6) phases in its Project Life Cycle, presented in Figure 1. These phases are:

(1) Problem Definition and Formulation, the phase at which the problem identified and understood
(2) System Design, the phase at which the ANN is modeled
(3) System Realization, the phase at which the ANN system is developed and trained
(4) System Verification, the phase at which the ANN is tested and the accuracy of the system is verified
(5) System Implementation, phase at which the ANN is im-

*Corresponding author: Cherl Nino M. Locsin
†email: cmlocsin@usc.edu.ph

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plemented via a computer program
(6) System Maintenance, the phase at which the system at which the ANN is implemented is updated with new developments.

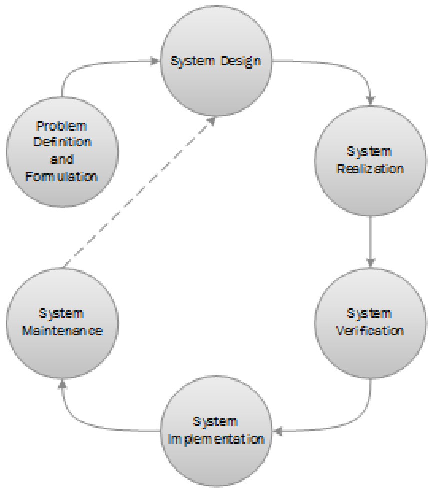

Fig. 1. ANN project life cycle

The interconnection of neurons, maybe organized to form layers, forms an ANN. Examples of ANN are: (1) Multi-layered Feedforward Artificial Neural Network (MLFANN) [16], and (2) Recurrent Neural Networks (RNN) [17]. A MLFANN is an ANN that introduces the concept ordering interconnected neurons into multiple layers, which are: (1) input layer, (2) n number of hidden layers, and (3) output layer. Whereas, a RNN contains cyclic connections ordered in: (1) input layer, (2) *n* number of hidden recurrent layer, and (3) output layer [17]. The structure of an RNN is presented in Figure 2.

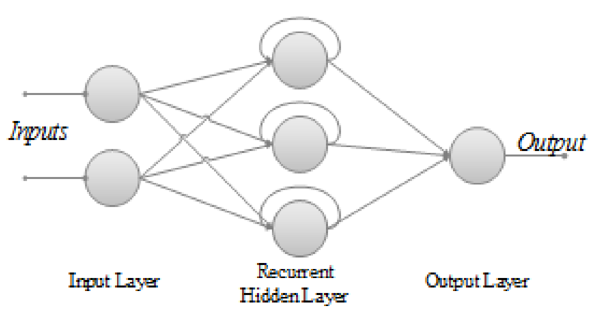

Fig. 2. RNN structure

In contrast to MLFANN, RNN has been greatly successful in sequence labeling and prediction tasks, making it more powerful than MLFANN [17]. Some applications of RNN are: time series prediction, speech recognition, and handwriting recognition [18].
A specific architecture of RNN, called the Long Short-Term Memory (LSTM) RNN, contains memory blocks in the recurrent hidden layer. These memory blocks can store temporal state of the network in its memory cells with self-connections, allowing it to learn long sequences of observations making it a perfect match for time series forecasting [17, 19].
The basic unit of any ANN is a neuron which maps its input to the output through various processes. This is presented in Figure 3.

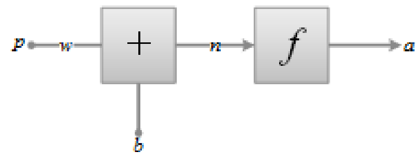

Fig. 3. RNN structure

Before presenting the input in to an ANN, data has to be pre-processed using normalization to assure that all inputs are at a compatible range [20]. Normalization will also help the system yield more accurate prediction [11].
The normalization of data undergoes two (2) steps:
(1) Analyze the source file, input fields, number of records in it and creating the input and output fields
(2) Normalize the actual data and the nominal data using equilateral normalization [21]. The equation that will be used is given by Equation 1.

$$f(x) = \left[\left(\frac{q - min}{max - min} \right) (high - low) \right] + Low \qquad (1)$$

After normalization, the neurons receive input data p through the input links. Each neuron may receive a single, or multiple set of data [13]. The input traverses into the neuron through its weight w. Because of the traversing of the input to the weight, their values become multiplied and produces the weight-input product *wp*. A bias *b*, b that shifts the direction of the output to help determine a better prediction, is added to the weight-input product [22]. This produces the neuron potential x_i. The neuron potential is then processed through the activation function. The activation function transforms a weighted sum of input data to an output signal [23]. The activation function may be linear, sigmoid, or tanh, among others. After the activation, the data is then released to the output [13].
On a larger scale, a neuron maybe connected to another neuron, or neurons, in order to define their operation and reflect their degree of importance [16, 19]. The weight w holds the interconnection between 2 or more neurons. This is presented in Figure 4.

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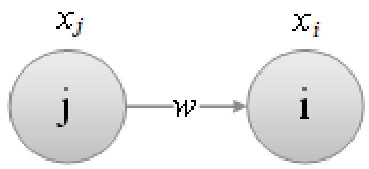

Fig. 4. Connection of neurons *i* and *j*

The receiving neuron, presented in Figure 2 as neuron *i*, has to process all of its incoming inputs, and their respective weights. A mapping function assigns the subset value which consists all of the neuron's ancestral value [16]. All of the ancestral weight-input values are then summed up in order to form the complete potential of the receiving neuron [16].
An ANN can operate in two modes, which are: (1) training, and (2) prediction. The training mode involves changing the weights between neurons. While the prediction mode allows the ANN to forecast possibilities through the learned information [24]. Having multiple recurrent hidden layers can improve the accuracy of the neural network's predictions [13].
There are two propagations made by the ANN during its training [19]. These propagations are:
(1) Forward Propagation, the presentation of the dataset to the ANN from input layer to output layer.
(2) Backward Propagation, the error between the actual and nominal values are presented back to the input layer of the ANN.
The epoch is a parameter that sets to what extent the neural network should be trained [11]. The epoch is number of the training cycles, which refers to at which the input and output were presented in a neural network.
The optimizer is a set of parameters that browses through the weights of the network in order to minimize the resulting loss of the ANN output [19, 25]. One of the recommended optimizers for any RNN is Root Mean Square Propagation (RMSProp), a variant of Stochastic Gradient Descent (SGD) [26].
RMSProp uses the following set of parameters:
• Learning Rate lr
This parameter is the quantifier of the weight vector change acceleration. The learning rate can be any value from 0 – 10 [27]. A small value should be set for the learning rate so the step value from each iteration is small, and to avoid the risk of overshooting [11].
• Rho rho
This parameter is a gradient moving average decay factor that helps improve the results of the network [28].
• Epsilon ep
This parameter is a fuzz factor that is a small number added for numerical stability of the weight update value, and avoid division by zero [29].
• Decay Rate dr
This parameter determines the decay of the learning rate over each update to lessen the weight update value overtime for stability of network training [27, 29].
The resulting loss, also known as the Cost Function C, from the ANN training result will then be back propagated to the input [29]. The resulting loss in RMSProp is evaluated using Mean Squared Error (MSE). MSE provides the average magnitude error between the P_i, predicted or nominal output, and A_i, actual output, MSE also takes less computing memory [11]. This is given by Equation 2, where *N* is the total number of samples.

$$C = MSE = \frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2 \tag{2}$$

The gradient grad between the Cost function and each of the weight in the ANN is then calculated, this will be used as part of the parameters for RMSProp [30]. This is presented in Equation 3.

$$\text{grad} = \frac{\partial C}{\partial w} \tag{3}$$

During ANN training mode, RMSProp operates with the following algorithm [31]:
(1) Compute the cache value using Equation 4.

$$cache_i + = (\text{cache}_{i-1} * dr) + (1 - dr) * \text{grad}_i^2 \tag{4}$$

(2) Get the updated weight value using Equation 5.

$$w_{i+1} = w_i - \frac{(lr * grad_i)}{\sqrt{cache_i} + ep} \tag{5}$$

The prediction mode is operated through regression. Regression investigates relationships between variables, which refers to the input factors in this study, that enables it to identify causal effect of one variable to another allowing it to be used in predictions [24].
To evaluate the prediction results, between the nominal demand P_i and actual demand A_i of an ANN, there are various evaluation techniques, which are: Accuracy, Mean Square Error (MSE) which was used for the evaluation of the training result. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Sum Square Error (SSE) [11].
Accuracy of the nominal output versus the actual output is calculated using Equation 6.

$$\text{Accuracy} = 100\% - \left| \frac{|A_i - P_i|}{A_i} x100\% \right| \tag{6}$$

Sum Squared Error (SSE) gives the indication of the total magnitude error between models and the measured results since SSE does not average the results. SSE is dependent on

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the number of observations so the quantity of error is significant. This is given by Equation 7, where N is the total number of samples.

$$SSE = \sum_{i=1}^{N} (A_i - P_i)^2 \tag{7}$$

Mean Squared Error (MSE), given in Equation 2, does not only provide the average magnitude output between the actual and nominal outputs, but it is also the statistical variance in a set of data [32].

Root Mean Squared Error (RMSE) provides how much error there is between the actual and nominal outputs. The smaller the RMSE is, the closer the actual and nominal outputs are [33]. It is also the standard deviation of the dataset. This is given by Equation 8.

$$RMSE = \sqrt{MSE} \tag{8}$$

The error margin between predicted water demand and actual water demand, according to a study conducted by Prieto, et al., should be less than 23.2% [34].

Artificial Neural Networks have the capability of being 99% accurate for short-term demand predictions, with a time scale of daily or hourly basis, for municipal water demand predictions [35].

Keras is a neural network modeling framework used to implement ANN models, giving researchers a way to organize layers [36]. Keras has been used by various graduate studies to model neural networks, some of these are: Deep Learning Architectures for Computer Vision [37], Predicting periodic and chaotic signals using Wavenets [38], and Prediction of Financial Markets Using Deep Learning [39].

The aim of this study is to implement the use of ANN to develop an ANN decision support system (ANN-DSS) that will forecast monthly water demand predictions, with at least 90% average accuracy between the actual and predicted demand for the year 2016.

The objective of this study is to develop an ANN-DSS software tool that is be able to:

• Provide municipal water demand predictions in volume (cubic meters) on a monthly basis. This can help MCWD in its water distribution decision-making process, as well as have future water demand predictions which can be used to increase their service coverage.

• Identify the distribution of the municipal water demand among the municipality's barangays by means of each of the barangays' socioeconomic profile. This will provide MCWD a new set of information, which is the per barangay water demand, to consider in distributing the water supply. The scope and limitations of this study are the following:

• The system only predicts water demand, given in volume (cubic meters) and conducted on a monthly basis. The system can only generate predictions further than the dataset duration, at 33% of the dataset duration.

• Cebu City was the specific study area for the prediction of municipal water demand, where all of the eighty (80) barangays of Cebu City were considered in the distribution of the municipal water demand.

• The implementation of the ANN-DSS tool was done manually. Keras was used as a framework for the neural network modeling only, and system attributes were manually developed and defined.

• Users are not able to change the parameters of the network since it will affect the model of the system.

• User Interface is only limited to begin the neural network training.

• All the output predictions, and evaluations of the ANN were automatically stored to multiple CSV files. These were segregated in municipality, and per barangay.

• This study had only engaged in phases one (1) to five (5) of the ANN project life cycle. Problem Definition and Formulation was described prior in the introduction. The methodology of this study will cover System Design to System Implementation. The last phase, System Maintenance, was not engaged since future updates and developments will not be covered by this study.

II. METHODOLOGY

A. Study Area and Input Data

This study analyzed factors affecting water demand in the municipality of Cebu City. To predict the municipal water demand of Cebu City, the following factors, also called features, were used as input dataset:

• Historical Water Use (m^3)

• Historical Water Production (m^3)

• Average Monthly Temperature (^oC) [40]

• Total Monthly Precipitation (mm) [41]

• Municipal Population (total number of people in the municipality) [42]

• Water Rates (₱) [43] (by rates below 11 m3, rates between 11 m^3 to 20 m^3, rates between 21 m3 to 30 m^3, and rates above 30 m^3).

Temperature and precipitation data were acquired from Department of Science and Technology – Philippine Atmospheric Geophysical and Astronomical Services Administration (DOST – PAGASA) Region VII, municipal population was acquired from the Philippine Statistics Authority (PSA), and historical water use, water production, and water rates

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were acquired from MCWD. All the data that were collected were monthly historical records from 2005 until 2016.

To identify the distribution of the municipality's water demand prediction to its corresponding barangays, the socioeconomic profile of every barangay was used as input dataset.

The socioeconomic profile consisted of the following set of information [44]:

• Nominal Barangay Water Demand (m^3)

• Barangay Population (total number of people in each barangay)

• Land Area (km^2)

The Nominal Barangay Water Demand was calculated using the following steps:

(1) The number of households per barangay was identified.

(2) For the per capita usage of every barangay, the number of households in each barangay was multiplied by 24 m^3 (household per capita water use).

(3) The results of step 2 for each barangay were added to identify the total per capita usage of the municipality.

(4) The result of step 3 was subtracted from the actual municipal water use to identify the water demand gap.

(5) The result from step 4 was then added to the per capita usage of each of the 80 barangays of Cebu City in terms of their respective household percentage towards the total amount of households in the municipality. This was considered as the nominal water demand for every barangay.

The 2000, and 2010 data for the population and number of households datasets were acquired from the socioeconomic profile of Cebu Province based from the 2000, and 2010 Census [44]. Barangay population, and number of household for 2015 were acquired from the Philippine Statistics Authority.

The annual growth rate, using Equation 9, was then determined from 2000 to 2010, and 2010 to 2015 since there was no available data for the population and number of population between 2005 to 2010, 2010 to 2015. While the equation used to get the population and number of households in between 2000 and 2015 is presented in Equation 10 [45].

Growth rate equation:

$$r = \frac{\frac{(y_n - y_0)}{y_0} * 100\%}{n} \quad (9)$$

where:

• r is the resulting growth rate between a certain time period

• n is the total number of time steps between a certain time period

• y_0 is the value at the start of the time period

• y_n is the value at the end of the time period Value at an instance between a time period.

$$v_m = y_0 * (1 + r)^m \quad (10)$$

where:

• r is the resulting growth rate between a certain time period, identified by Equation 9.

• m is the instance time step

• v_m is the value at m

From the gathered data, three (3) sets of data were utilized in this study. These datasets were used for training, verification, and testing [16].

• Training Dataset comprised of 67% of the dataset from 2005 to 2014, this dataset was used in training the neural network in the given number of epochs.

• Testing Dataset comprised of 33% of the dataset from 2005 to 2014, this dataset was used in testing the trained neural network, the resulting predictions from the testing dataset were used to identify the accuracy of the ANN.

• Verification Dataset was comprised of the dataset from 2015–2016, in which the data was compared with the prediction output from the testing and training for the years 2015-2016.

B. Artificial Neural Network Development

1) System design: The basis of the ANN model in this study was a Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) due to its memory blocks in the recurrent hidden layer. These memory blocks allow itself to learn long sequences of observations making it a perfect match for time series forecasting [17].

The ANN in this study was activated using tanh activation function because it converges faster, which made predictions more accurate at less amount of epochs [46]. The tanh activation function is given by Equation 11.

$$f(x_i) = \frac{e^{x_i} - e^{-x_i}}{e^{x_i} + e^{-x_i}} = \tanh(x_i) \quad (11)$$

where:

e refers to the Euler's Number

x_i is the potential of the neuron.

There were two (2) general models that were constructed, each had served following purposes: (1) prediction of municipal water demand, and (2) prediction of per barangay water demand, with 1 dedicated model for each barangay. Two separate models were constructed since the prediction of barangay water demand is experimental, and used nominal inputs for two out of three of its dataset input (barangay population, and nominal water demand) which produces a

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default error to the prediction values. Whereas, the municipal water demand prediction used mostly historical values, except for the municipal population.

Each of the two models only had one (1) hidden recurrent layer. There is no empirical rule with regards to the number of hidden recurrent layers and its corresponding neurons in an ANN [47]. The selected criterion used to choose the number of hidden neurons was that the hidden neurons should be two-thirds of the input neurons plus the total output neurons [47].

For the prediction of municipal water demand, the ANN had a total of seven (7) hidden neurons. The format of a input layer neurons: b hidden layer neurons: c output layer neurons, a resulting model of 9:7:1 was applied [17]. Nine (9) input layer neurons were allocated for every factor affecting municipal water demand. Seven (7) hidden neurons were allocated using the two-thirds rule in allocating hidden neurons. The output layer was allocated one (1) neuron to produce the municipal water demand predictions.

Each barangay, for the prediction of their respective water demand, had the model 3:3:1. Three (3) input layer neurons were allocated for each of the barangay's socioeconomic profile. The recurrent hidden had three (3) neurons, which followed the same rule for the hidden layer in the prediction model. The output layer was allocated one (1) neuron which produced water demand predictions for every barangay. The ANN models that were used in this study are presented in Figure 5, and Figure 6.

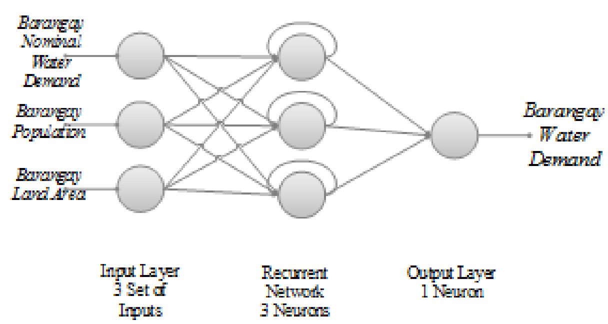

Fig. 5. Per barangay water demand forecasting LSTM-RNN structure

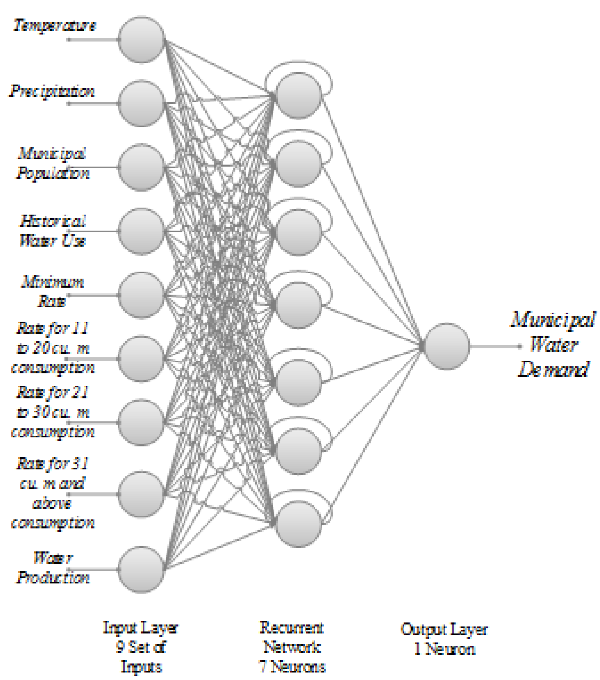

Fig. 6. Municipal water demand forecasting LSTM-RNN structure

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2) System realization: The flow of the MLFANN in this study, presented in Figure 7, followed four (4) main processes:
(1) Neural Network Initialization
(2) Data Pre-Processing
(3) Neural Network Training
(4) Neural Network Evaluation

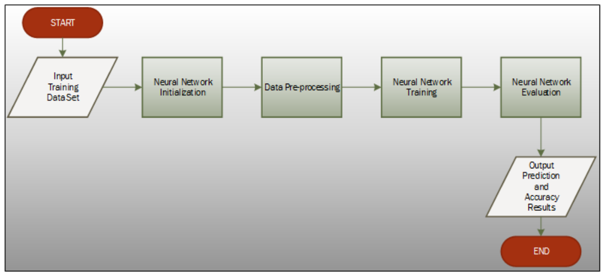

Fig. 7. System diagram

C. Neural Network Initialization

After the training datasets were presented to the ANN, certain factors in the ANN were initialized. These factors were:
• Network Weight
The initial network weights were assigned with fixed random values using a numpy seed, a function that sets random numbers to variables, of seven (7) to have fixed output values for the ANN prediction [48].
• Epochs
Each of the one (1) municipal, and eighty (80) barangay prediction models were set with 1000 epochs. A total of 81,000 epochs were utilized for all models.
• Learning Rate
The learning rate should be set to a small value, either 0.1, 0.01, or 0.001, that would not make the network overshoot nor converge too slowly [49]. A learning rate of 0.001 was set for the ANN since it produced the highest accuracy results among the suggested learning rates.
• Rho
The value of rho should be between 0 and 1, where the moving average will decay slower as it is closer to 1 [36]. A rho value of 0.9 was set for the ANN as recommended rho value for LSTM [33].
• Epsilon
The value of epsilon should be set to a very small value to avoid division of zero in the case that the cache value will be zero [24]. An epsilon value of 1×10^{-8} was set for the ANN, based from the recommended value for epsilon [36].
• Decay Rate
A decay rate of 0 was set for the ANN since it is recommended that the decay rate for RMSProp in RNN be set to 0 to avoid decaying of the learning rate [36].

D. Data Pre-Processing

For each of the two (2) neural network models, the respective actual and nominal input datasets were normalized using equilateral normalization in Equation 1. The high and low values were set to 1 and 0, respectively.

E. Neural Network Training

This study used RMSProp for the ANN training backward propagation, since it is recommended for RNN [36]. RMSProp was implemented using the RMSProp optimizer arguments initialized during the ANN initialization. The ANN training had 1000 epochs per model.
Initially, the input datasets were forward propagated towards the ANN. The datasets were activated using Equation 11. Then, the resulting output was evaluated using Equation 2. The resulting Cost function was then back propagated to the input using Equation 5. This process was repeated for 1000 times, as per set epochs.
In order for the ANN to operate in the prediction mode, regression was followed by this study [24]. This was applied in order to predict the water demand in Cebu City, and its corresponding barangays [24].

F. Neural Network Evaluation

For ANN training result evaluation, MSE was used in this study as the Cost function. The result, solved using Equation 2, was back propagated to the network to perform the RMSProp training algorithm.

G. System Verification

The target accuracy result of this study, as stated in the objectives, was to have at least 90% average accuracy between actual water demand and nominal water demand for the year 2016. The accuracy of the system was verified using

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Equation 6. The variance of the system was also identified, using the MSE formula in Equation 2, together with the standard deviation using the RMSE formula in Equation 8.

H. System Implementation

The ANN, which followed the specifications presented in the System Realization, was implemented by developing a desktop software application. The following were used to implement the ANN:

• Enthought Canopy, an environment that provides tools for iterative data analysis, data visualization, and application development [50]
• Keras, a neural network modeling framework [36]
• Theano, a Python library used for defining, optimizing evaluating mathematical expressions using multidimensional arrays [51].

The system was implemented with a simple user interface to initialize neural network training. All prediction and evaluation outputs were saved to CSV files, segregated per barangay, and municipality.

III. RESULTS AND DISCUSSION

There were two (2) sets of predictions made by the ANN, these were: (1) Municipal Water Demand, and (2) Per Barangay Water Demand. Each of the two sets of results was evaluated with their accuracy, MSE, SSE, and RMSE.

A. Municipal Water Demand

Table 1 presents the evaluation results for the prediction of municipal water demand for Cebu City. From the training results, which consisted of 67% of the total dataset, the ANN was able to be 99.85% accurate in contrast to the actual water consumption data. On the other hand, during the ANN testing, which consisted of 33% of the total dataset, the ANN was able to be 99.13% accurate in contrast to the actual water consumption data. A total of 111,729,677,117.94 m6 SSE between the nominal and actual water data was collected from the testing of the ANN. A MSE or variance of 2,793,241,927.95 m6 was also collected from the ANN testing, with RMSE or standard deviation of 52,851.13 m^3, and average error of 39,819.14 m3. The average error of the ANN training and testing results is only 1.05% in comparison to the average predicted water demand of 3,808,966 m^3 by the ANN training and testing prediction. This is lower than MCWD's average error of 2.99% for their water demand prediction in the same time duration, from 2005 to 2014.

TABLE 1
MUNICIPAL WATER DEMAND EVALUATION RESULTS SUMMARY

Municipal Water Demand	
Metric	Result
Training Accuracy	99.85%
Testing Accuracy	99.13%
SSE	111,729,677,117.94 m^6
MSE	2,793,241,927.95 m^6
RMSE	52,851.13 m^3
Average Error	39,819.14 m^3
Average Training and Testing Water Demand Prediction	3,808,966 m^3

Table 2 presents the comparison for the 2016 actual water use versus the forecast generated by the system, and the forecast of MCWD. It is shown that the average accuracy between the actual water use and ANN forecast is 95.74%, which is higher than the average accuracy between MCWD's forecast and the actual water use, which is 88.69%. The maximum accuracy of the 2016 ANN forecast is 99.08% for the month of September, while the maximum accuracy of the MCWD forecast is 96.33% for the month of March. The minimum accuracy of the ANN forecast is 87.12% for the month of February, while the minimum accuracy of the MCWD ANN forecast is 81.93% for the month of December. The ANN was not able to predict at least 90% accuracy for the month of February due to the drop of -15.49% from the actual consumption of January that was not anticipated by the ANN during its forecast. This can be attributed to the fact that February has the least number of days, as well as February 2016 had the lowest average temperature of 27.35^0C. The minimum and maximum accuracy scores of the ANN forecast are both higher than the minimum and maximum accuracy scores of the MCWD forecast.

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TABLE 2
COMPARISON OF ACTUAL WATER USE VERSUS ANN FORECAST AND MCWD FORECAST FOR 2016

2016	Actual Water Use (m^3)	ANN Forecast (m^3)	Accuracy (%)	MCWD Forecast (m^3)	Accuracy (%)
Jan	5,112,137	4816654	94.22	5,342,346	95.49
Feb	4,426,485	4996413	87.12	5,011,655	86.78
Mar	5,088,952	4829806	94.91	5,275,655	96.33
Apr	4,860,494	4994794	97.24	5,305,147	90.85
May	4,841,808	4933285	98.11	5,508,659	86.22
June	4,861,026	4619737	95.04	5,528,874	86.26
July	5,128,501	5060199	98.67	5,622,531	90.36
Aug	5,252,412	4963604	94.50	5,750,842	90.51
Sep	5,097,226	5050320	99.08	5,767,553	86.84
Oct	5,169,089	4939953	95.57	5,864,552	86.54
Nov	4,920,081	5137288	95.59	5,602,800	86.12
Dec	5,086,206	5143499	98.87	6,005,162	81.93
Total	59,844,417	59,485,553	99.40	66,585,776	86.80
AVE	4,987,034. 75	4,957,129	95.74	5,548,814 67	88.69
MAX	5,252,412	5,143,499	99.08	6,005,162	96.33
MIN	4,426,485	4,619,737	87.12	5,011,655	81.93

Appendix A presents the complete, based from historical data from 2005 to 2016, ANN forecast for the monthly municipal water demand of Cebu City from 2005 to 2020.

Appendix B presents the ANN forecast from 2005 to 2016 based from the set training and testing datasets from 2005 to 2014. The forecast presented in Appendix B was compared to the forecast of MCWD, and actual water use in Appendix C. The accuracy for both ANN and MCWD forecast towards the actual water use were computed using Equation 6. In some cases, MCWD provided more accurate predictions than the ANN predictions, this is due to how ANN learns from behavior changes from historical data. In which, in 17 out of the 144 predictions where the MCWD had better accuracy, the ANN was not able to anticipate the succeeding water use as much from what the ANN had learned during its training from previous behavioral changes of the input datset. Table 3 presents the comparison of accuracy results of RMSProp, Adam, and SGD optimizers. Adam optimizer, is an optimizer similar to RMSProp, except it uses momentum instead of gradient in the updating of weights [31]. On the other hand, SGD is the optimizer which RMSProp is a variant of. SGD updates weights by subtracting the product of the learning rate and gradient from the previous weight [31].

From the accuracy results, RMSProp has higher accuracy compared to Adam and SGD for both Training and Testing. This means that RMSProp is more accurate than both Adam and SGD for the modeled ANN.

TABLE 3
COMPARISON OF RESULTS ACCURACY

Accuracy Metric	Accuracy
RMSProp	
Training Accuracy	99.85%
Testing Accuracy	99.13%
Adam	
Training Accuracy	99.46%
Testing Accuracy	98.47%
SGD	
Training Accuracy	98.86%
Testing Accuracy	97.96%

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Figure 8 presents the comparison of the actual water use from 2015 to 2016 towards the forecasted water demand from the developed ANN. This shows how the ANN forecast follows through the behavioral changes of the actual water use in Cebu City. It shows how the water use for February 2016 dropped which the ANN was not able to follow through, this resulted to its lowest accuracy for 2016 at 87.12%. However, the ANN was still able to generate an average of 95.74% accuracy against the actual water use for the year 2016.

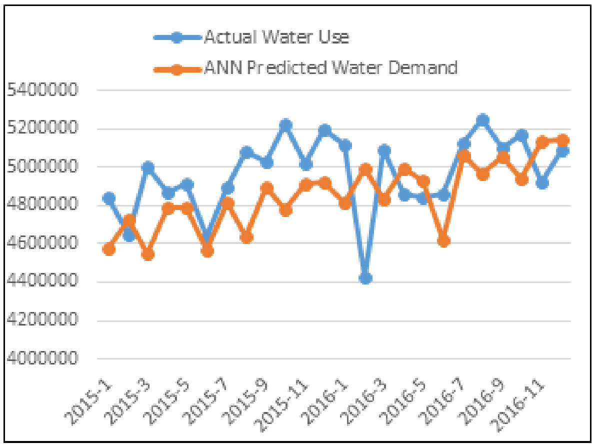

Fig. 8. Comparison between the Actual and Predicted Cebu City Water Demand from 2015 to 2016

B. *Per Barangay Water Demand*

Table 4 presents the accuracy of ANN training and ANN testing prediction results versus the nominal water demand for every barangay. It is shown that the accuracy for both ANN training and ANN testing are more than 90%, with average accuracy of 99.67% and 98.38% for ANN training and testing forecasts, respectively. The maximum generated ANN training prediction accuracy was 99.96% from Barangay Lusaran, while the maximum generated ANN testing prediction accuracy was 99.71% from Barangay San Jose. The minimum generated ANN training prediction accuracy was 94.41% from Barangay Guadalupe, while the minimum generated ANN testing prediction accuracy was 96.79%, which was still from Barangay Kamagayan. For the cases of barangay Carreta, Pulangbato, and Kamagayn, their testing accuracy scores are higher than their training accuracy scores as a result of how the ANN learned from the input dataset during the training. For these barangays, in the timeframe where the ANN was conducting its testing process, the ANN was directed from what it previously learned to generate test predictions that are closer to the nominal water demand than the training predictions.

TABLE 4
TRAINING AND TESTING PREDICTION ACCURACY RESULTS FOR THE BARANGAYS OF CEBU CITY

Barangay	Training Accuracy (%)	Testing Accuracy (%)
Adion	99.95	97.78
Agsungot	99.91	97.66
Apas	99.83	98.75
Babag	99.92	98.05
Bacayan	99.76	99.31
Banilad	99.73	99.53
Basak Pardo	99.95	97.63
Basak San Nicolas	99.93	97.91
Binaliw	99.92	97.85
Bonbon	99.91	97.82
Budla-an (Pob)	99.72	98.7
Buhisan	99.87	98.47
Bulacao	99.94	97.9
Buot-Taup Pardo	99.91	97.63
Busay (Pob)	99.78	99.21
Calamba	99.92	97.87
Cambinocot	99.91	97.72
Camputhaw(Pob)	99.72	99.63
Capitol Site(Pob)	99.7	99.7
Carreta	99.03	99.18

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TABLE 4
CONTINUE..

Barangay	Training Accuracy (%)	Testing Accuracy (%)
Central(Pob)	99.12	97.1
Cogon Pardo	99.57	99.64
Cogon Ramos(Pob)	99.91	97.82
Day-as	99.47	97.93
Duljo(Pob)	99.72	99.65
Ernita(Pob)	99.18	97.19
Guadalupe	94.41	98.99
Guba	99.73	99.57
Hippodromo	99.74	99.57
Inayawan	97.06	98.19
Kalubihan(Pob)	97.91	97.07
Kalunasan	98.87	99.18
Kamagayan(Pob)	98.76	96.79
Kasambagan	99.94	96.93
Kinasang-an Pardo	99.86	98.49
Labangon	99.91	97.82
Lahug (Pob)	99.95	98.51
Lorega (Lorega San Miguel)	99.93	97.9
Lusaran	99.96	97.7
Luz	99.85	98.64
Mabini	99.91	97.81
Mabolo	99.89	98.39
Malubog	99.91	97.64
Mambaling	99.91	97.76
Pahina Central (Pob)	99.87	98.8
Pahina San Nicolas	99.67	99.26
Pamutan	99.95	97.8
Pardo(Pob)	99.86	98.87
Pari-an	99.87	98.7
Paril	99.9	97.49
Pasil	99.91	97.67
Pit-os	99.76	99.29
Pulangbato	99.47	99.66
Pung-ol Sibugay	99.45	99.57
Punta Princesa	99.73	99.55
Quiot Pardo	99.79	99.15
Sambag I (Pob)	99.87	98.89
Sambag II (Pob)	99.95	98.56
San Antonio (Pob)	99.94	97.86
San Jose	99.72	99.71
San Nicolas Central	99.93	97.91
San Roque (Ciudad)	99.95	98.53
Santa Cruz (Pob)	99.88	98.36
Sapangdaku	99.79	99.1
Sawang Calero(Pob)	99.94	98.43

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TABLE 4
CONTINUE..

Barangay	Training Accuracy (%)	Testing Accuracy (%)
Sinsin	99.91	98.21
Sirao	99.93	97.62
Suba Pob.(Suba San Nicolas)	99.9	97.71
Sudlon I	99.9	97.68
Sudlon II	99.91	97.1
T. Padilla	99.88	98.7
Tabunan	99.72	99.66
Tagbao	99.93	98.05
Talamban	99.75	99.37
Taptap	99.93	97.94
Tejero (Villa Gonzalo)	99.94	98.41
Tinago	99.87	98.67
Tisa	99.91	97.68
To-ong Pardo	99.95	97.63
Zapatera	99.89	98.45
AVERAGE ACCURACY	99.67	98.38
MAXIMUM ACCURACY	99.96	99.71
MINIMUM ACCURACY	94.41	96.79

Appendix E presents the predicted distribution of water demand among the barangays of Cebu City for 2016. From the results, the barangay with the highest demand is barangay Lahug at 2,879,891.93 m^3 due to the fact that Lahug has the highest average household of 7,589 households since 2000. On the other hand, the barangay with the least demand is barangay Paril at 82,586.32 m^3 due to a very low average household of 262 average households since 2000. The predicted barangay water demand is consolidated with the predicted municipal water demand by getting the accuracy of the monthly total demand from all the barangays in comparison to the generated municipal water demand prediction. The generated total of the prediction by barangay is 95.76% accurate towards the ANN Forecast, while it is 93.90% accurate towards the actual water use.

IV. CONCLUSION AND RECOMMENDATIONS

The developed LSTM-RNN ANN was able to generate municipal water demand predictions at 95.74% average accuracy for the year 2016 in contrast to the actual water demand, presented in Table 2, and per barangay water demand predictions with 93.90% accuracy for the year 2016 in contrast to the actual water demand, presented in Appendix C. The generated accuracy for both ANN models are higher than the predictions by MCWD with average accuracy at only 86.79%. Therefore, it is concluded that the factors considered for both models, as well as the ANN models developed generated better predictions than of the MCWD's. Furthermore, the developed LSTM-RNN ANN is best for water demand forecasting because of the memory blocks in its recurrent hidden layer that allowed the LSTM-RNN ANN to generate observations from learning the long sequences of historical data among the factors considered in this study, which led to more accurate predictions compared to the prediction from MCWD.

For further studies, it is recommended that the water production will also be forecasted. The forecasting of water production can provide upcoming data of water supply which can be used to counter check the available supply for the upcoming water demand. A better interface should also be developed for better access to the users of the system, as well as give the users the ability to generate other possible scenarios for water demand prediction. And lastly, it is recommended that economic factors will be considered for both the prediction of municipal water demand, and distribution of per barangay water demand to identify how the economic profile of an area affects its water demand.

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