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An Intelligent Approach to Develop, Assess and Optimize Energy Consumption Models for Air-Cooled Chillers using Machine Learning Algorithms

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Abstract: The building sector accounts for more than 70% of the total electricity use. Chillers consume more than 50% of electrical energy during seasonal periods of building use. With the growth of the building sector and climate change, it's essential to develop energy-efficient HVAC systems that optimize the ever-increasing energy demand. This study aims to develop an energy consumption prediction model for air-cooled chillers using machine learning algorithms. This is done by developing different static and dynamic data-driven regressive and neural network models and comparing the accuracy of their prediction to identify the most accurate modeling algorithm using 3 main inputs chilled water return temperature, outside drybulb temperature, and cooling load. The proposed model structure was then optimized in terms of the number of neurons, epochs, time delays as well as the number of input variables using a genetic algorithm. Training and testing were done using real data obtained from a fully instrumented 4-ton air-cooled chiller. Results of the study show that the optimized artificial neural network model can predict energy consumption with a high level of accuracy compared to conventional modeling techniques. The development of highly accurate self-tuning models can be a powerful tool to use for other applications such as fault detection and diagnosis, assessment, and system optimization. Further studies are necessary to evaluate the effectiveness of using deep learning algorithms with more hidden layers and cross-validation techniques.

Keywords: Building Energy Consumption, Chiller Energy Modeling, Machine Learning in HVAC, Regression Modeling, Hyperparameter Optimization

Introduction

Energy consumption is on the rise and building systems are considered one of the main contributors to total CO_2 emission (EPA; Katipamula and Brambley, 2005). Energy consumption end use by buildings has also been on the rise globally (Pérez-Lombard *et al*., 2008). Various studies focused on improving energy efficiency by end use (Zolfaghari *et al*., 2022; Zolfaghari and Jones, 2022) HVAC systems and particularly chillers are the main electricity consumers. The result of a study done by Fasiuddin and Budaiwi (2011) is that proper system selection and operation of the HVAC system in buildings can provide up to 25% in energy savings (Fasiuddin and Budaiwi, 2011). Based on a survey conducted by the department of energy, more than 12000 chillers are operating inefficiently which translates to more than 30% in additional energy use. As an example, a dirty condenser coil of an air-cooled chiller can reduce efficiency by 15%. It is of high significance to develop energy management methods that help with a better understanding of HVAC systems and ensure efficient operation of chillers. Various studies have been conducted to improve the efficiency of the HVAC system by using statistical and dynamic energy predictive models, advanced control algorithms, and optimization techniques (Zhang *et al*., 2013; Zeng *et al*., 2015; Kusiak *et al*., 2011; Harish and Kumar, 2016; Okochi and Yao, 2016).

Air-cooled chillers are more widely used for smaller-scale residential and commercial buildings as they require less square footage in the buildings compared to chilled water plants which translate to fewer components and ultimately lower initial cost. This study aims to develop and optimize a modeling algorithm that can predict the energy consumption of this type of chiller. A brief overview of different modeling approaches is followed.

Energy models can be generally classified as I) physical models and II) data-driven models. Physical models, which are based on the principle of heat transfer, estimate energy performance at building, system, and component levels. There exist many software's to develop energy models by solving physical heat transfer equations (Crawley *et al*., 2008). Data-driven methods, on the other hand, map historical energy performance data to external variables such as temperature and humidity, among others. Data-driven models can be further categorized as statistical and machine learning models, of which the most common are artificial neural networks and support vector machines. Research published in the last decade suggests that the aforementioned machine learning-based energy models produce more accurate predictions compared to the counterpart engineering and statistical methods.

Analytical Modeling Approach

Physics-based models are used to simulate and develop analytical models. Analytical models are mostly used to predict the energy consumption during the design phase of buildings' HVAC systems and can be used after the equipment is installed and running. It is important to note that these detailed physics-based models, due to their non-linearity and a high degree of complexity make them expensive to implement (Wang and Ma, 2008). An example of an analytical approach is the development of a simulation model for cooling coils by Yu *et al.* (2005); the model development of a transient absorption chiller by Kohlenbach and Ziegler (2008); Bendapudi *et al*. (2005); Zhang *et al*. (2009).

Data-Driven Modeling Approach

Unlike the analytical approach, data-driven algorithms are developed using real data collected from an operating machine. Relationships between different variables also known as inputs and output then identified. Artificial neural network algorithms are widely used to predict the power consumption of building energy systems (Günay, 2016; Castelli *et al*., 2015; Tahmasebi *et al*., 2019ab). Comparison between different modeling algorithms in terms of accuracy and performance was done in different studies. Kaytez *et al.* (2015) compared different algorithms including regression analysis, support vector machine, and artificial neural network, and concluded that both ANN and support vector machine algorithms can predict energy consumption with high accuracy (Kaytez *et al*., 2015). Deng *et al*. (2018), compared different machine learning models with linear regression models to predict building energy performance (EUI) and concluded machine learning models are marginally more accurate by having 10-15% lower prediction error while linear regression models outperformed machine learning models in predicting plug loads. It was also deduced that the Support Vector Machines (SVM) algorithm is a powerful tool to predict energy consumption alongside ANN models. He *et al*. (2014) studied the use of intelligence neural network algorithms to optimize the performance of HVAC systems and compare different data-driven models. Seong *et al*. (2017), used a time series, neural network model, to predict a building energy consumption and concluded that this machine learning model has an as better performance compared to the analytical modeling approach. Another study done by Jeong and Chae (2017) assessed the importance of input variable selection in improving the accuracy of predictive models. This study also compared four different machine learning algorithms and reported ANN as the superior model. Another study done by Tahmasebi used ANN to model and detect and diagnose faults in a water-cooled chiller (Tahmasebi *et al*., 2019ab).

Azadeh *et al*. (2008) studied ANN, and in a study referenced against industry data, the ANN model demonstrated superior results over conventional regression models (Azadeh *et al*., 2008). Srinivasan assessed multiple traditional models and ANN-based models in energy demand forecasting. He claimed that ANN models produced better results compared to time-series and regression models (Srinivasan, 2008). Aydinalp *et al*. (2002) applied ANN to model energy consumption in residential buildings. In comparison with previously developed engineering models, the ANN model had better performance (Aydinalp *et al*., 2002). Jovanović *et al*. (2015) demonstrate the viability of ensemble neural networks for predicting energy consumption. They achieve better prediction results using the ensemble method versus a single neural network, indicating that ensemble methods prove useful for heating energy consumption predictions (Jovanović *et al*., 2015). Talib *et al*. (2020) studied the power prediction accuracy of ANN, support vector machine, and aggregated bootstrapping and concluded that these models are effective tools in energy prediction for HVAC components.

Development of Energy Consumption Predictive Models

Data Collection and Input Identification

Data was collected from a 4 nominal ton air-cooled chiller from an HVAC lab at the University of Cincinnati. The chilled water system consists of one air-cooled chiller with two pumps. The chiller serves the VAV AHU coil and three fan coils located in zones. The HVAC system serves three 8 by 8 ft. well-insulated and controlled environmental zones. Following Fig. 1 and 2 provide a schematic of the layout of all equipment in the lab.

The chiller was operating during the month of June and July when the outside temperature ranged roughly from 50-95°F. Chiller specifications are presented in following Table 1.

Different input variables were selected and recorded in 1 min intervals while the chiller was running. These variables are Chilled water return temperature, chilled water supply temperature, outside drybulb temperature, outside wetbulb temperature, chilled water flow rate, cooling load, time of day, and type of day.

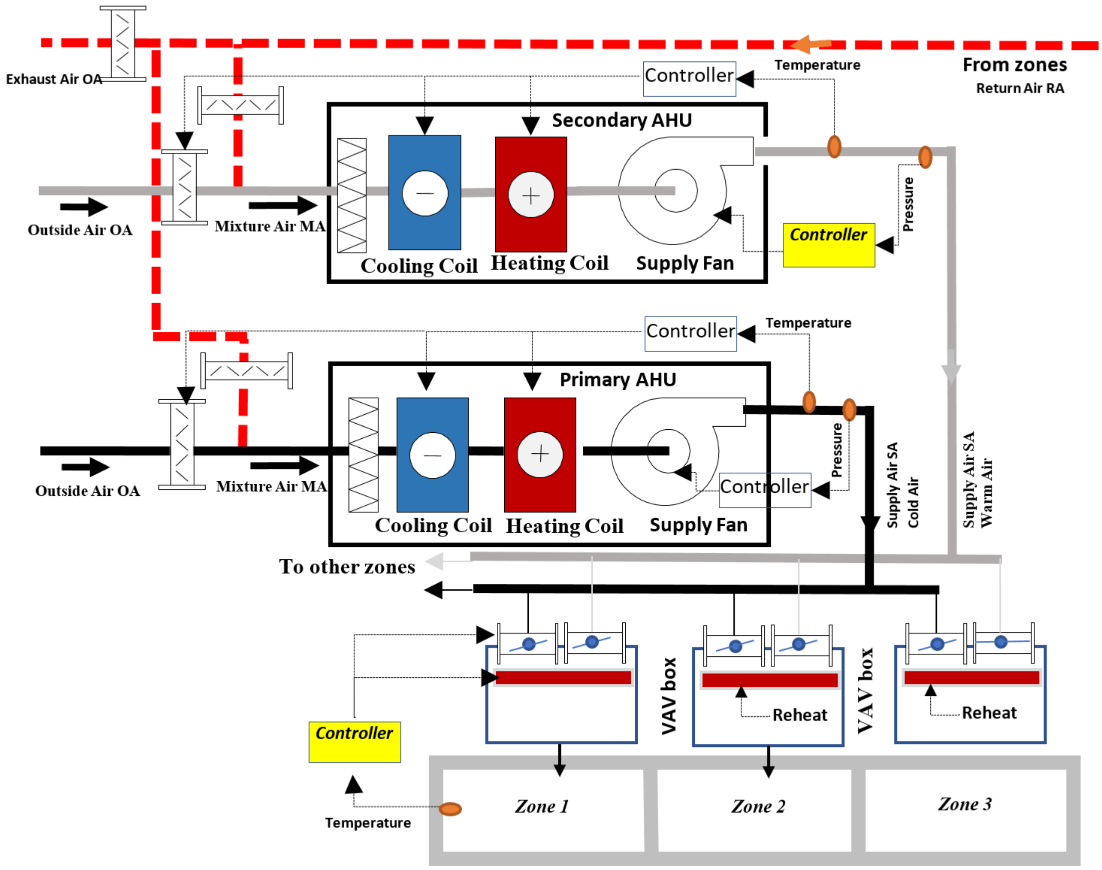

Fig. 1: HVAC system layout

Table 1: Chiller specifications

Type	Cooling capacity	Entering temp	Leaving temp	Pressure drop	Flow
Air-cooled	44000 Btu/h	54°F	42°F	32 psi	8 gpm

A dataset consisting of values for mentioned input variables was then created. To create a simple yet robust model, the correlation between each input variable and the power consumed by the chiller was evaluated. This was done by developing regressive and artificial neural network models. Input variables were then ranked based on the R-square value calculated by developed models. Input variables that had the highest correlation coefficient were then selected to be used in the model development phase and other input variables were omitted. Input variables with the highest correlation coefficient that were selected are Chilled water return temperature, outside drybulb temperature, and cooling load. Figure 3 shows a schematic of the selected inputs and output.

Model Development and Optimization

To evaluate the accuracy and performance, different machine learning algorithms were used. The accuracy and performance of each model are recorded and compared. The modeling algorithm that has the best performance would be further optimized to have the highest prediction accuracy. Each model in the model category has different sub-model algorithms that will be explained below.

Regression Modeling

Different regressive-based modeling techniques were used. They vary from simple linear regression to more complex variation of linear regression (stepwise, robust), decision tree regression (fine, medium, coarse), Support Vector Machine regression models (linear, quadratic, cubic) Ensemble modeling including bagged tree and boosted trees as well as the Gaussian Process regression (squared exponential, rational quadratic, exponential).

Artificial Neural Network

Artificial neural networks are computational models that are inspired by natural human brain neurons. A high number of processing units work together in a connected fashion to process information and generate results.

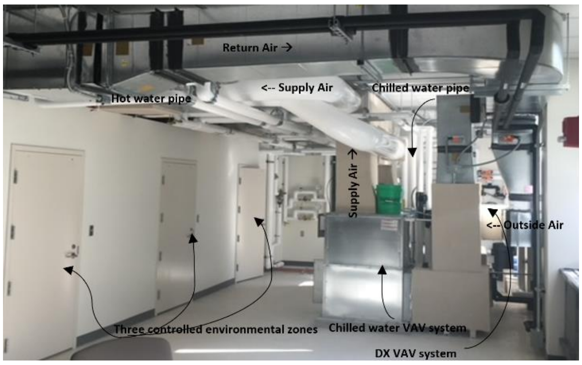

Fig. 2: HVAC lab equipment

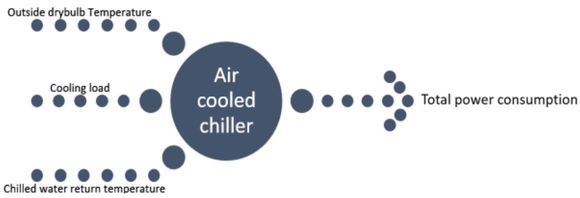

Fig. 3: Air-cooled chiller input and output variables

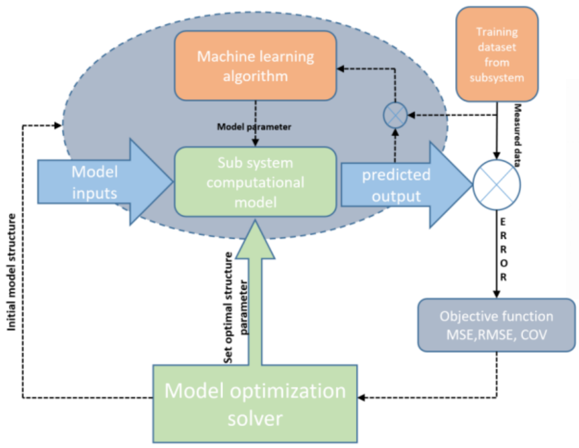

Fig. 4: Model structure optimizer

A neural network contains the following 3 layers:

The input layer (the raw information that feeds into the network), the hidden layer (determines the activity of each hidden unit and the weights of the connections between the input and the hidden units), and, Output layer (depends on the activity of the hidden units and the weights between the hidden and output units).

3 different subsets of neural network modeling are used to test and train the datasets. They are the 1-simple artificial neural network, 2-autoregressive neural network, and 3-recurrent neural network. Each of these methods uses a different computational algorithm that makes it suitable to use for modeling different components of the HVAC system. To compare the performance and accuracy of different models, R-squared value, MSE, RMSE, and COV for each model were calculated. These parameters are defined by the following equations:

$$R^2 = 1 - \frac{\sum (y - \hat{y})^2}{\sum (y - \bar{y})^2} \tag{1}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y - \hat{y})^2 \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \| y(i) - \hat{y}(i) \|^2}{N}} \tag{3}$$

$$CV = \frac{\sigma}{\mu} \tag{4}$$

N in the above formulas is the number of data points, $\hat{Y}i$ is the predicted value by the proposed model, *Yi* is the data used for calibration and *Y* is the arithmetic mean of *N*.

Choosing Best Performing Models

By comparing the performance of each modeling algorithm, models were ranked from best performance and accuracy to least accurate. Best models then were chosen and further optimized to have improved predictive performance. The optimizing model structure was done differently for regression-based modeling and artificial neural network models.

Optimizing Model Structure

In regression-based models, model parameter tuning was done by optimizing numeric parameters, changing kernel function, the number of inputs selected and changing the validation scheme from no validation to holdout validation and cross-validation with different folds (k). For K number of folds, the algorithm divides the data into K disjoint sets and trains the model by using out-of-fold data points and accesses model performance using in-fold data. This process protects against overfitting by evaluating the accuracy of each partitioned dataset.

In artificial neural network models, model structure optimization was done by: Tuning the input variables, adjusting the ratio of data used for training and testing, changing the number of neurons for the training and testing phase, changing several epochs, and changing the time delay value. Figure 4 illustrates the integration between the data-based model and the model parameter optimizer tool. This integration starts with using a typical machine learning model to predict the energy consumption of the chiller and to tune model parameters. This is followed by the second level of the optimization process to determine the optimal model structure. In practice, the optimizer engine automatically trains and test the model with different variation of the number of neurons, time delays, and epochs using a genetic algorithm and generate the best model structure as an output while minimizing the error in model output prediction. A genetic algorithm is an optimization method based on the theory of natural selection and has been used in various studies to minimize energy consumption (Reynolds *et al.*, 2018; Arabali *et al*., 2012; Nassif, 2014), This automated process is imitated in a step-by-step analysis format in this article.

Results and Discussion

The following sections present and evaluate model prediction accuracy based on performance comparison results and hyperparameter optimization for best-performing models.

Comparing Different Regressive and Neural Network Models

Various regression-based and ANN models, specified were developed and compared to identify the best performing models. Results provided in Table 2 identify some of the best-performing models among all models developed.

Based on performance results, it can be concluded that both regression-based models, as well as ANN models, can predict the energy consumption of air-cooled chiller with good accuracy but some have higher accuracy and performance. Rational quadratic Gaussian regression algorithm had the best accuracy and performance among regression-based modeling algorithms while artificial neural network models, specifically, autoregressive neural networks have the best performance and accuracy in predicting the energy consumption of the chiller.

Model Structure Optimization of Best Performing Model

Auto-Regressive Neural Network (ARNN) algorithm als known as the NARX model which is a time series forecasting model is the best performing algorithm. ARNN algorithm process overview is brought in Fig. 5 below.

Figure 6 presents the actual and predicted energy consumption for training and testing sets. Dataset was equally divided for the training and testing period.

The following sections evaluate the effect of different hyperparameter optimization techniques on the accuracy and performance of the model.

The implication of using Different Ratios for Testing and Training Period

The amount of data used for training and testing was changed to evaluate prediction accuracy. For the first scenario, 50% of the dataset was used to train the model and the remaining 50% was used to test the model. This ratio then changed to 60% for training and 40% for testing. The amount of data for training then subsequently changed to 70, 80, and 90%. RMSE, COV, and coefficient of determination for both the training and testing period were calculated and presented in Table 3.

It can be noted that the performance and accuracy of the ARNN algorithm increase as the ratio of data used for training increases. Best performance and COV is when 80% of data is used to train the model and 20% is used for testing. This trend reverses as the ratio of the dataset used for testing decreases from 20 to 10%. Therefore it can be concluded that the optimal ratio for training and testing this algorithm is around 80% for training and 20% for testing. R^2 values for both training as well as testing period remained consistent and was not considerably affected by changing the amount of data used for training and testing.

The Implication of using a Different Number of Epochs

Epoch in machine learning is a hyperparameter that indicates the number of times that the machine learning algorithm works through the entire training portion of the dataset. The number of epochs can vary from 1 to1000 and larger. This is to make sure that the learning algorithm runs through the training dataset enough times until the model prediction error is minimized. However, a larger number of epochs translates to a longer computation time. A different number of epochs should be tested for different datasets until the best epoch performance is identified. Plotting model errors for different numbers of epochs to identify learning curves can be beneficial to diagnose whether the model has overlearned, learned, or is sufficiently balanced. In this study, a different number of epochs were used for the ARNN model. Several epochs ranged from 1-1000 and the computational time required for the machine was recorded. It was noticed that implementing a large number of epochs did not yield the best result, although, it took a significantly longer time for the software to compute the error. To achieve minimal model error and minimize complexity and computational time, it was noted that for this dataset, a minimal error can be achieved when a few epochs are used. Table 4 provides numerical values for RMSE during the training and testing period as well as coefficient of variance for 3, 6, 9, and 12 epochs. It also contains the same values for the optimal number of epochs.

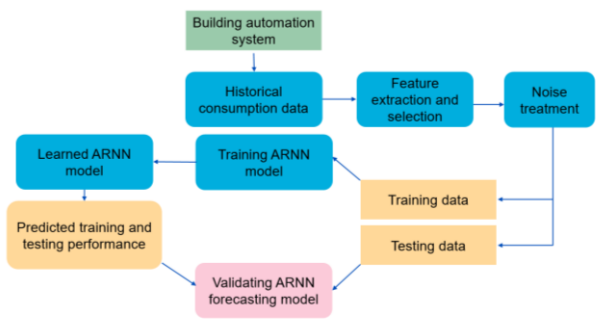

Fig. 5: Flowchart of Auto-Regressive Neural Network model

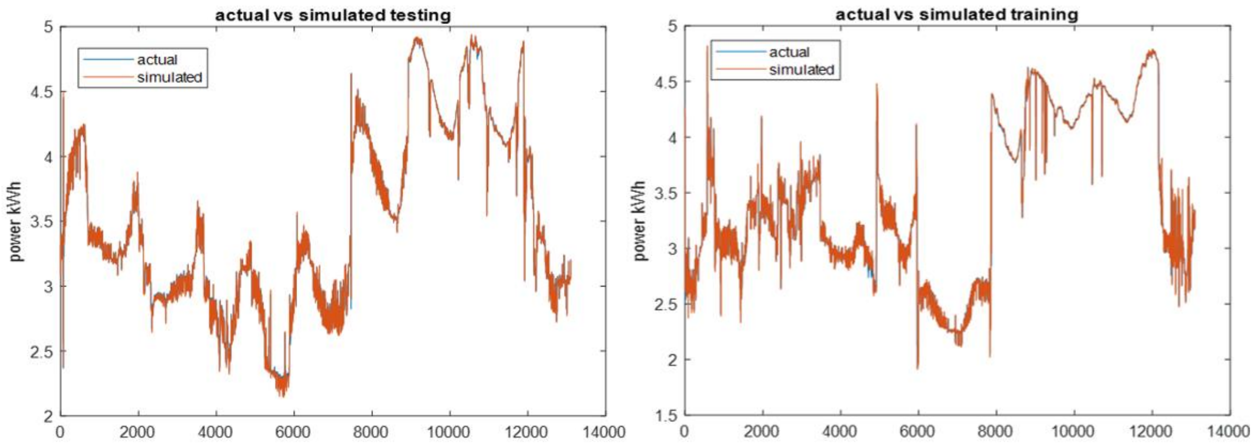

Fig. 6: Actual vs simulated for training and testing period

The Implication of Changing the Number of Neurons for the Testing and Training Period

A different number of neurons was used to train and test the best-performing ARNN model. Neurons compute the weighted average of their input. This sum then is fed through a nonlinear activation function. The number of neurons varied from 1-20; evaluating the performance of the model for each number. For the training period, it was observed that the performance of the model consistently increased as the number of neurons increased. Best training performance was achieved when N = 19. RMSE for the best number of the neuron was 0.0039. Figure 7 and 8 illustrates the performance according to the different numbers of neurons used for the training phase.

For a testing period, the same number of neurons, ranging from 1-20 was used to test the accuracy of the ARNN model. No significant pattern was noticed between the increasing number of neurons and model performance. Performance haphazardly varied from 0.0023 to 0.0027. The best model performance for the testing period was achieved when the number of neurons was 6. As an increasing number of neurons can ultimately prolong the computational time, it is essential that changing this hyperparameter is carefully considered individually as well as simultaneously with other hyperprameters such as the number of epochs, time delay, and percentage of the dataset used for training and testing.

The implication of Changing Number of Time Delays

To further analyze the effect of changing hyperparameters on the accuracy and effectiveness of the model, adjusting the time delay parameter of the ARNN model is important. Time delay in non-linear time series neural networks concerns the delay in time that the model is going to use before predicting the value. Time delay values selected for this study ranged from 1 to 3. To examine the effect of varying time delays alongside using different neurons, the algorithm was programmed to implement a different number of neurons (1-12) for each tested time delay. Figure 9 shows the performance of the training and testing period for a different number of time delays and several neurons.

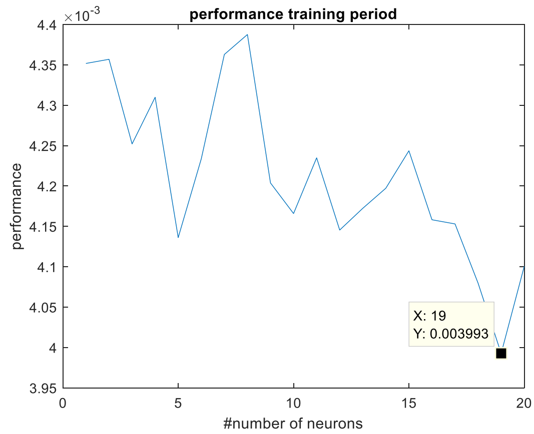

Fig. 7: Performance training period for different numbers of neurons

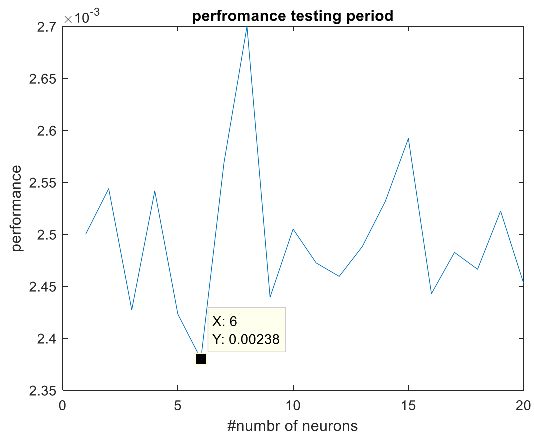

Fig. 8: Performance testing period for different numbers of neurons

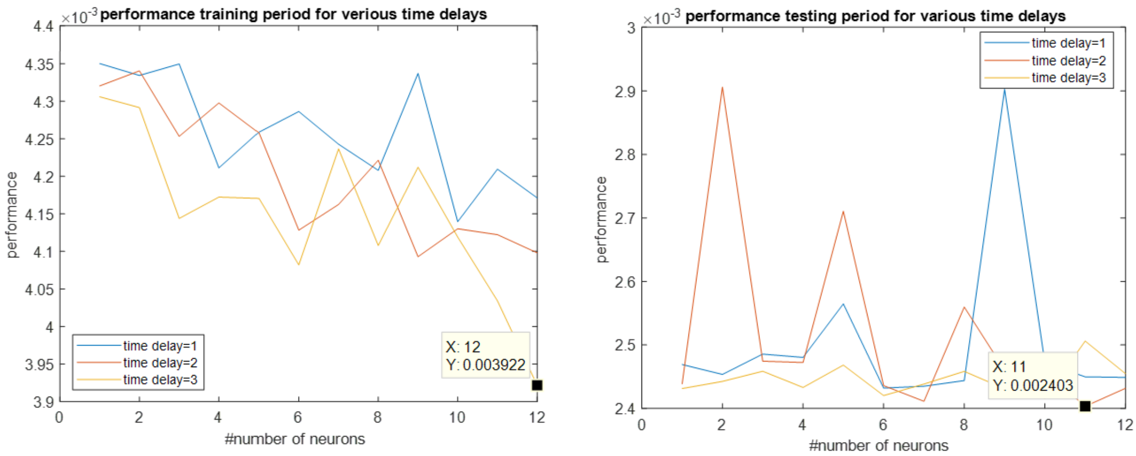

Fig. 9: Model performance for different numbers of neurons and time delays for training and testing period

Table 2: Performance and accuracy of best performing models

Modeling algorithm	R2	MSE	RMSE
Stepwise regression	0.89	0.055	0.2350
SVM	0.97	0.015	0.1220
Gaussian regression	0.98	0.012	0.1090
Ensemble Baggedtree	0.97	0.014	0.1180
Fine tree	0.97	0.016	0.1280
ANN	0.96	0.001	0.0430
ARNN	0.98	1.7 × 10E-6	0.0042

Table 3: Performance, COV, and R^2 value for a different proportion of dataset for training and testing

Configuration	RMSE test	COV	R^2 train	R^2 test
50% training 50% testing	0.0042	0.0136	0.995	0.994
60% training 40% testing	0.0031	0.0157	0.994	0.995
70% training 30% testing	0.0033	0.0154	0.994	0.995
80% training 20% testing	0.0025	0.0123	0.994	0.993
90% training 10% testing	0.0034	0.0150	0.995	0.995

Table 4: Model performance for different numbers of epochs

Configuration	RMSE testing	RMSE training	COV
Epoch = 3	0.0129	0.0068	0.0280
Epoch = 6	0.0364	0.0130	0.0470
Epoch = 9	0.0374	0.0069	0.0325
Epoch = 12	0.0048	0.0047	0.0171
Optimal epoch	0.0024	0.0042	0.0127

It is noted that during the training period, performance improved as the number of neurons increased which is in agreement with the observation. It is also noted that the model performs better in the training period when the time delay is more than 1. Best performance is achieved when the highest number of implemented neurons (N = 12) and time delay (TD = 3) were used.

For the testing period, however, changing the number of neurons did not make a significant change in performance. It is evident that implementing a higher value of Time Delay (TD = 3) results in better and more consistent performance. The best performance for the testing period was achieved when N = 11 and TD = 2.

Conclusion

This research was conducted to find and tune the best dynamic model to capture the energy consumption behavior of an air-cooled chiller. Different machine learning algorithms were used to develop various computational models. The performance of these models then was calculated and compared to find the most accurate modeling algorithm. A different range of modeling algorithms was used. Regression-based modeling algorithms were implemented and tested against artificial neural network models.

The result of model performance and accuracy comparison concluded that ANN models have better prediction ability compared to regression-based models which are in alignment with the results of other studies provided in the background section. ARNN in particular outperformed other neural network variations.

Concerning optimizing the performance of the most accurate modeling algorithm, different model structure optimization approaches were used. Initially, the number of inputs was optimized in a way that model achieved a better performance while minimizing computational time.

The effect of changing the ratio of the dataset used for testing and training was also examined. Results indicate that increasing the ratio of data used for training can increase the performance of the model. It was noted that the ratio of data used for training varied from 50 to 90%. The best performance was achieved when 80% of data was used to train the data and 20% for testing. This result confirms that a larger dataset used for training can yield better performance. However, models should be individually optimized as each model can behave uniquely due to their varying dynamics.

The effect of changing the number of neurons on the performance of the ARNN model was also evaluated. The number of neurons was changed from 1-20 and model performance was captured and recorded for both the training and testing period. It was concluded that increasing the number of neurons improved the performance of the training portion of the dataset but had no significant effect on the performance of the model during the testing period. This pattern can also vary drastically based on the complexity and dynamic of each dataset.

Concerning optimizing the time delay used in the time series neural network, a different number of neurons were introduced to the model and various time delay (1-3) was used to capture the performance of the model. It was noted that an increasing number of time delays in general improved the performance of the model. During the training period, the best performance was achieved when the highest number of time delays and neurons were used. For the testing period, however; the highest number of time delays made performance values better and less haphazard.

It was concluded that an autoregressive artificial neural network that has an optimized number of inputs and uses around 80% of data for training and 20% for testing with 11 epochs and a time delay of 3 has the highest accuracy of 99.9%. This study can be expanded by implementing other data-driven modeling techniques such as deep learning algorithms with more hidden layers and cross-validation methods.

Author's Contributions

Mostafa Tahmasebi: Conceptualization, Review and Editing, Methodology, software, Investigation, Original draft preparation.

Nabil Nassif: Conceptualization, Review and Editing, Methodology, Supervision.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues are involved.

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