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OPTIMAL CONTROL OF CHILLER PLANTS USING BAYESIAN NETWORK

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ABSTRACT

Linear regression models trained by the dataset, which contain the optimal values for the control parameters under different operating conditions, have been heavily studied in the literature of chiller plants operation optimization due to their performances with higher speeds. However, the linear regression models face difficulties when a nonlinear input/output relationship is considered. Addressing this challenge, we proposed a Bayesian Network (BN) model (a data-driven and probabilistic graphical model), for the operation optimization of chiller plants. Here, we first introduced the construction of the BN model, and demonstrated its validity on the model predictive control of a condenser water set point for a water-cooled chiller plant. Then, we evaluated the performance of the proposed BN model under imperfect prediction of weather conditions and building cooling loads with inputs embedding manually generated errors. The baseline performance was provided through a model-based optimization (MBO) using an exhaustive search. The results show that the proposed BN model could provide energy savings compatible with the one given by the MBO using an exhaustive search for both inputs with and without errors.

INTRODUCTION

In the United States, commercial building cooling equipment consumed around 77.4 GWh primary energy in 2010, which accounted for about 2.7% of the Nation's total primary energy usage (U.S. Department of Energy). 35% of the commercial building cooling energy consumption is attributed to chiller plants (Westphalen, et al. 2001). Thus, reducing the energy consumption of the chiller plants is of great importance to the Nation's energy usage and efficiency initiatives. Improving the chiller plant control is a cost-effective approach for improving the chiller plant efficiency since it does not require replacing of the existing equipment.

There are different ways to enhance the control of the chiller plants. One way is to apply a model-based optimization (MBO) method to find the optimal control for chillers. An MBO adopts a chiller plant model (i.e., can be a physics-based or regression model) to predict the energy usage with given parameters in the control system under the predicted or measured load and weather conditions. Supplementary optimization algorithms are then employed to find the optimal values of control parameters to minimize the energy usage or the cost (Ma, et al. 2009, Ma, et al. 2010, Ma, et al. 2011, Huang, et al. 2014). Although the MBO has been proven to be a feasible way to improve the operational efficiency of chiller plants, the optimization engine may take significant amount of time and computational resource usages to find the optimal control parameters, especially when a high-fidelity physics-based model (Ma, et al. 2008, Huang, et al. 2010) is used in the plant model. This makes the MBO less popular in the model predictive control where fast computing speed is necessary.

In order to address this problem, regression methods have been proposed in the literature (Hydeman, et al. 2007, Zhang, et al. 2011). In general, these methods search for optimal control parameters by developing a linear regression model that reflects the relationship between the optimal control parameters and given cooling load and weather conditions. These regression models are trained using datasets, which are usually generated by a large number of MBOs for various cooling load and weather conditions. To simplify the process, the optimization is commonly assumed to be steady meaning that for each output of the optimization, the corresponding inputs are assumed to be time-independent (ASHRAE 2011). The trained regression models are then exercised to provide optimal control parameters for a given cooling load and weather condition. While the generation of the training dataset may take significant amounts of computational time; once trained, the regression methods are able to predict the optimal control at negligible time spans. This makes them quite attractive for real world applications (Hydeman, et al. 2007, Zhang, et al. 2011). However, the commonly used linear regression models, may not perform well when the nonlinear input/output relationships are considered (Chang 2006).

To address the limitation of regression methods for systems with nonlinear input-output relationship, in this work, we propose a data-driven probabilistic graphical model, namely a Bayesian Network (BN) model, in substitution of linear regression models. The fact that the proposed BN model combines probability and graph theories (Koller, et al. 2009), makes it particularly suitable for handling the nonlinear relationships in the building systems (Toftum, et al. 2009, Shi, et al. 2012, O'Neill 2014).

In the next section, we introduce the construction of BN model for control optimization. To demonstrate the BN model's potential for the control optimization of chiller plants, we applied it to optimize the condenser water set point of a chiller plant. The performance of the BN model is then compared with the MBO method using an exhaustive search under the conditions with and without uncertainty in the inputs in terms of the cooling load and weather conditions.

METHODOLOGY

BN Theory

As shown in Figure 1, a BN model includes two parts: *node*s and *arc*s. The nodes (e.g. X_a to X_e in Figure 1) graphically represent discrete variables that comprises the system. The arcs indicate the casual relationship between the nodes. A node that sends an impact to one or more nodes is called *parent node* and a node that receives the impact is named as a *child node*. A node can be a parent and child node at the same time.

For a given node X_0, we define X_p={X_1,…,X_n} as its set of parent nodes. The conditional probability for X_0, $P(X_0| X_p)$, is defined as:

$$P(X_0|X_P) = P(X_0, X_P)/P(X_P), \quad (1)$$

where $P(X_0, X_p)$ is the joint probability of X_0 and X_p while $P(X_p)$ is the joint probability of X_1,…,X_n. The probability distribution is defined as an assignment of the possibility of each possible value for a variable. Nodes without any input arcs have independent probability distribution (e.g. X_a, X_e and X_f) while nodes (X_b, X_c, and X_d) with one or more input arcs have conditional probability distributions (CPD).

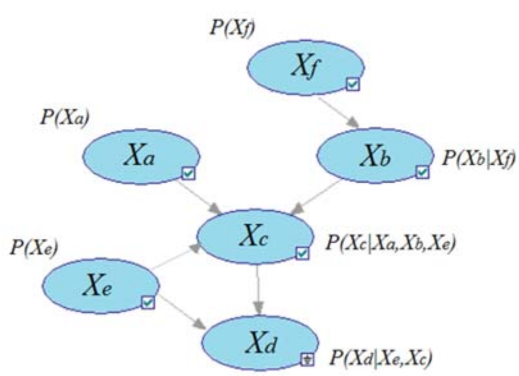


Figure 1 The structure of BN model

Procedure to Develop the BN Model for Controls Optimization

The procedure to develop the BN model for the control optimization consists of the following four steps:

Step 1: is to generate a database that consists of the input variables, such as the cooling load and weather conditions, and the corresponding optimal control settings as output variables, such as the optimal condenser water set point. Here, the database is generated using an MBO similar to those of other regression models (Hydeman, et al. 2007, Zhang, et al. 2011).

Step 2: is to discretize the values of the variables for the BN model if the data is continuous. The discretization of the continuous variables is essential for developing the BN model and affects the performance of the BN model significantly if is not done correctly (O'Neill 2014). A simple way to do the discretization is to make the interval uniformly distributed and select relatively small interval lengths so that the BN model could better represent the training dataset. However, using small intervals may require more time in searching the results. Here, the number of intervals may be reduced by managing the distribution intervals in order to balance the trade-off between the accuracy and searching time.

Step 3: is to train the BN model. We first divide the training data generated in Step 1 into several segments according to the discretization setting in Step 2. For each segment, we count the frequencies of each possible value for the optimal control parameters. Then, the appropriate frequencies are used to estimate the CPD of each possible value based on Equation (1).

Step 4: is to build a table rule to identify the recommended optimal control parameters. To convert the CPDs of multiple possible values to a single value for optimal control parameters, we calculate the conditional expectation values, i.e., the most likely optimal control parameters value, using the following equation:

$$E\left(X_0 \middle| X_P = x_p\right) = \sum_{i=1}^{n} x_i P\left(X_0 = x_i \middle| X_P = x_p\right), \quad (2)$$

where x_i is a possible value of X_0, n is the total number of the possible values, and x_p is the value of X_p. The conditional expectation values are the optimal control parameters recommended by the BN model.

CASE STUDY

Case Description

To evaluate the proposed BN model for chiller plant optimization, we studied a chiller plant located in Washington D.C., USA. It provides cooling to three nearby office buildings. As shown in Figure 2, it has three identical chillers (cooling capacity as 2,799kW) and three identical cooling towers. Each chiller has a dedicated chilled water pump, a condenser water pump and a cooling tower. In the condenser water loop, a three-way valve is employed to modulate the flow rate through the cooling towers to avoid overcooling, which happens when the temperature of the condenser water leaving the cooling tower is less than 12.78°C (55°F). The speed of the cooling tower fans is adjusted so that the temperature of the condenser water leaving the cooling tower would be less or equal to a predefined condenser water set point.

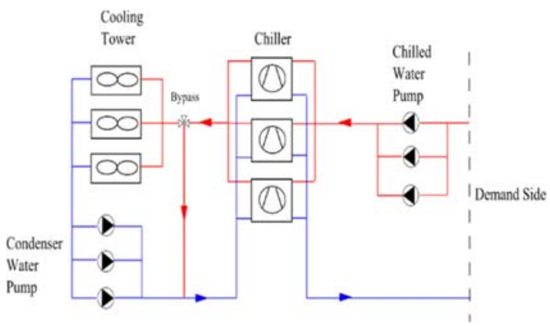


Figure 2 Schematic drawing the studied chiller plant

BN Model for the Condenser Water Set Point Optimization

In this study, the output variable is the condenser water set point, T_{set}, while the input variable are the cooling load, *Load* and the wet bulb temperature, T_{wet}. It is noteworthy that *Load* is a function of T_{wet} (Tongshoob, et al. 2004). Therefore, the T_{wet} is a parent node for *Load* and it is possible to only use T_{wet} as the input. In this study, we ignore the causality relationship between *Load* and T_{wet} since we had the measured data for both. With that in mind, we build the structure of the BN model as shown in Figure 3. Here, the BN model has been implemented using the Python modeling language (Python Software Foundation).

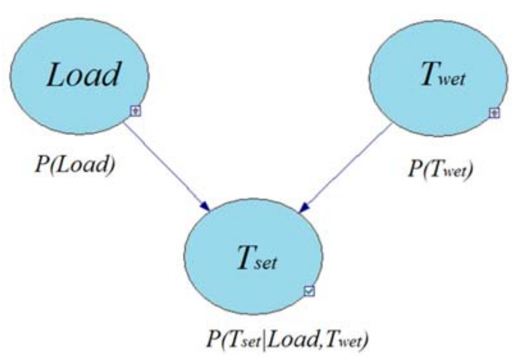


Figure 3 The structure of the BN model for the condenser water set point optimization

BN Model Setting and Training

To generate the training dataset, we first built a high-fidelity physical model for the chiller plant using the Modelica *Buildings* library (Wetter, et al. 2014). Figure 4 shows the top-level diagram of the Modelica model, which is similar to the schematic drawings presented in Figure 2. For more details about the model, please refer the study of Huang, et al. 2014.

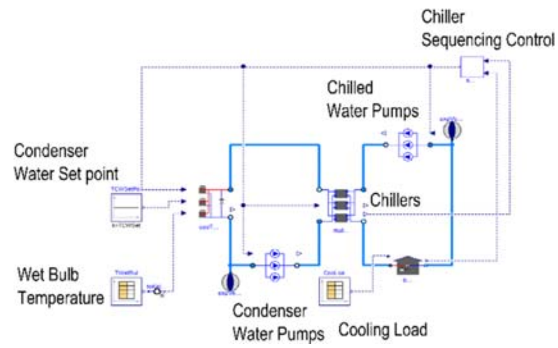


Figure 4 Diagram of Modelica model for the studied chiller plant

Using the plant model, we performed an MBO to find an optimal T_{set} so that energy use by the chillers and cooling towers can be minimized. In the MBO, an exhaustive search was employed to ensure the finding of the theoretical optimal solution. To generate a dataset that covers the possible range of chiller operation conditions with sufficient resolutions, we performed an MBO for 10,248 different combinations of *Load* and T_{wet}. The *Load* ranges from 14.2 ton (50 kW) to 2388.4 ton (8400 kW) with an interval of 14.2 ton (50kW). The T_{wet} varies from -5 °C to 25 °C with an interval of 0.5 °C. For T_{set}, the possible range is [15.11 °C, 26.11 °C] with an interval of 1 °C. The generated dataset is shown in Figure 5.

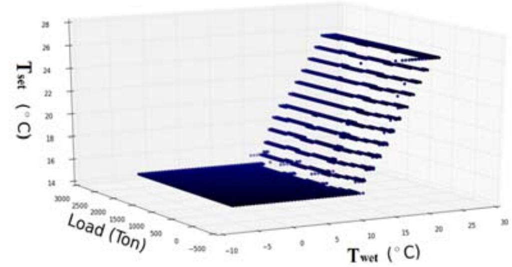
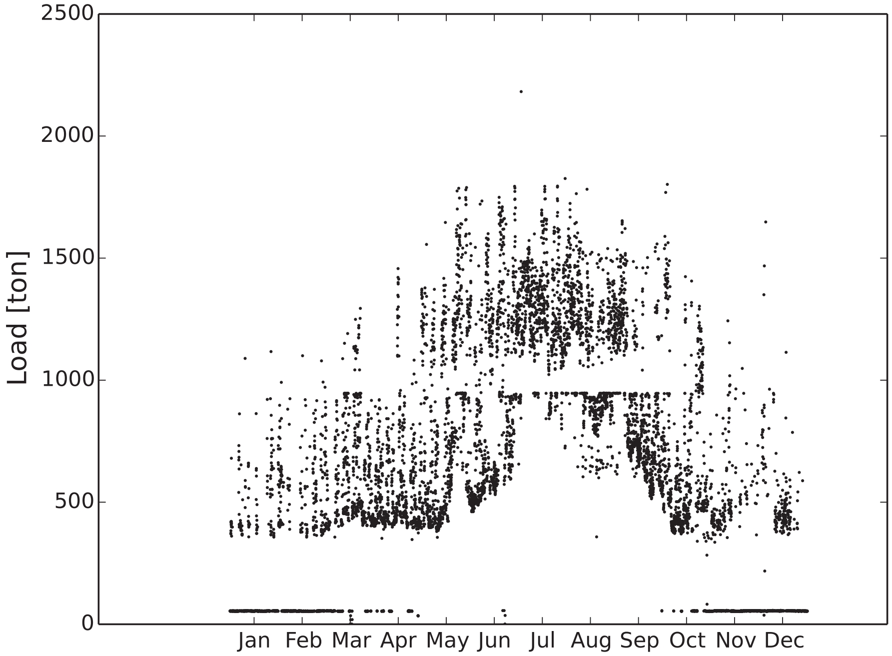


Figure 5 The training dataset

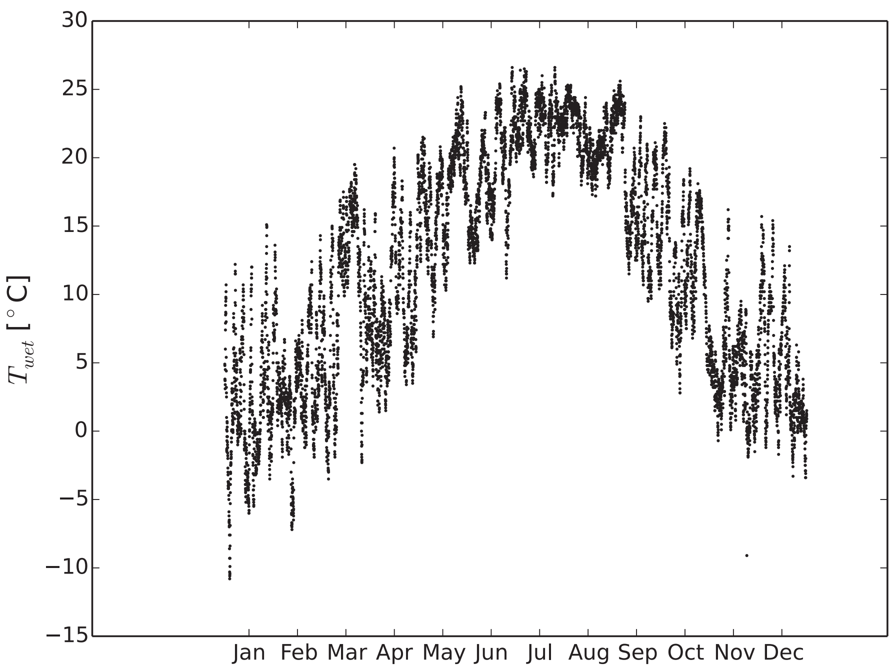
For the BN discretization, we used uniform distribution for intervals for both *Load* and T_{wet} with interval sizes of 56.86 ton (200 kW) and 1 °C, respectively.

Evaluation

We used the historic data of hourly cooling load and wet bulb temperature in the evaluation. Figure 6 (a) shows the on-site measurement of annual hourly cooling load data for the year 2014 while Figure 6 (b) shows the annual hourly wet bulb temperature for the same period from a dataset called Quality Controlled Local Climatological Data (National Climatic Data Center).



(a)



(b)

Figure 6 (a) hourly cooling load (b) hourly wet bulb temperature

The utilization of historic data has provided significant information on the a-priori for the inputs (i.e., a perfect prediction model for *Load* and T_{wet}). The uncertainties in prediction of the inputs *Load* and T_{wet} are incorporated using the formulas defined in equations (3) and (4):

$$Load^* = Load(1 + random(-0.2, 0.2)), \quad (3)$$

$$T^*_{wet} = T_{wet} + random(-1,1) + 4, \quad (4)$$

where $Load^*$ and T^*_{wet} are the cooling load and wet bulb temperature with error. The *random* (*a*, *b*) is a function that returns a random value between the input range [a, b]. Figure 7 shows the generated $Load^*$ and T^*_{wet} for a period of a day.

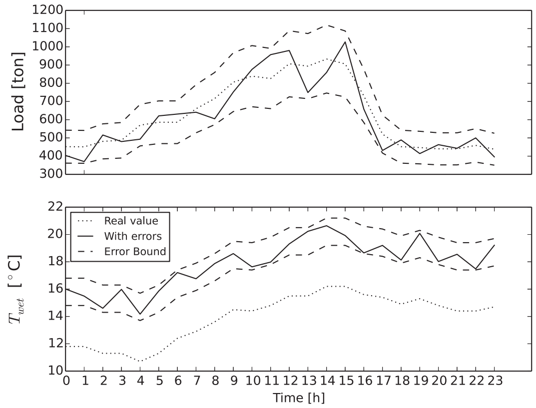


Figure 7 The cooling load and wet bulb temperature with error for April 20, 2012

As described in Table 1, we designed four scenarios to compare the BN and MBO with an exhaustive search with and without errors in inputs. The results of MBO with an exhaustive search are used as the baseline as they are the theoretical optimal solution.

Table 1 Different scenarios for evaluation

SCENARIOS	DESCRIPTION
Baseline (MBO)	MBO using an exhaustive search (theoretical optimal solution)
BN	BN model with perfect inputs
MBO+Error	MBO using an exhaustive search with errors in inputs
BN+Error	BN model with errors in inputs

Results

In this study, we assumed that the cooling load and wet bulb temperature are constant during an hour. Building on this assumption, the annual energy consumption by the chillers and cooling towers can be calculated by

$$E = \sum_{i=1}^{8760} 3600P_i, \qquad (5)$$

where E is the annual energy consumption by the chillers and the cooling towers, P_i is the power of the chillers and the cooling towers at the i^{th} hour, which is generated by the steady simulation.

Table 2 compares the total energy consumption by the chillers and cooling towers, the energy consumption deviation (in percentage) from the baseline, and the ratio of the number of predictions that failed to predict the theoretical optimal T_{set} to the total number of predictions. When there was no error in the cooling load and wet bulb temperature, T_{set} predicted by the BN model was close to that in the baseline. Only around 8.53% of the T_{set} predicted by the BN model were different from those in the baseline. This only caused a 0.06% increase in energy consumption, which means that the BN model has performance that is well compatible with MBO with an exhaustive search (i.e., theoretical optimal solution).

When there were errors in the prediction of cooling load and wet bulb temperature, both the BN model and an exhaustive search failed to predict the theoretical optimal T_{set} with a failure ratio as high as 50% percentage. However, the annual energy consumption is not very sensitive against imperfections in the prediction of T_{set}. When the T_{set} prediction failure ratio is set to 50% by both methods, only an additional 4% increase is experienced in total energy consumption.

Table 2 Different scenarios for evaluation

SCENARIOS	BN	MBO+ERROR	BN+ERROR
Energy Consumption [MWh]	2,464.00	2,564.20	2,560.20
Deviation From Baseline (%)	0.06	4.13	3.97
Prediction Failure (%)	*8.53*	*51.6*	*50.4*

Complementary to our earlier results, in order to capture the differences in model performances, we showed a detailed result of a single day (i.e., April 20, 2012). Figure 7 shows the hourly cooling load and wet bulb temperature with/without input errors during that day.

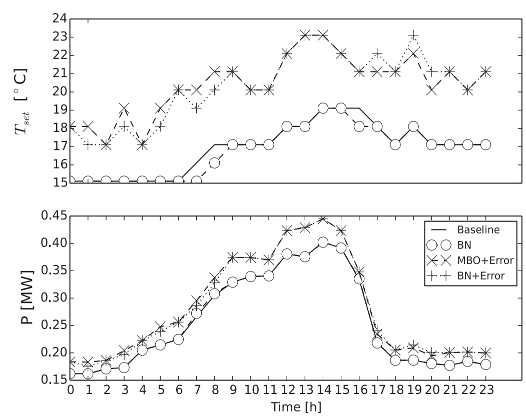


Figure 8 The predicted T_{set} and total power, P, for different scenarios

As shown in Figure 8, 21 predictions by the BN were recorded as the same as the baseline and there were only three hours that the BN predicted T_{set} 1 ºC higher than that of the theoretical optimal. However, with errors in load and wet bulb temperature prediction, neither of the considered methods could predict the theoretical optimal solution with precision for the whole day. The BN and MBO with an exhaustive search have similar performances against the error inputs.

CONCLUSION

In this study, we proposed a BN method for the chiller control optimization and evaluated the method using a case study of optimizing the condenser water set point. Our results have shown that the proposed BN model has similar performance, in terms of the accuracy of predicting optimal control, as that of the MBO using an exhaustive search with and without uncertainties in predicating cooling load and wet bulb temperature. Meanwhile, the BN can significantly reduce the computational times (from 11.6 hours by MBO to less than a second by BN).

The current work plants the seed of a study to apply the BN model in the optimization of the chiller plant operation. The future venues of this work concerns itself with the following improvements:

1) Evaluating the possibility of using limited training data set for the development of the BN model.
2) Taking the causality relationships between various input variables into account so that the BN model can still be used even when part of the input variable is not readily available.

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