Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

GAUSSIAN PROCESS MODEL FOR A WATER COOLED CENTRIFUGAL CHILLER USING BOTH MANUFACTURER'S AND OPERATION DATA

Young-Sub Kim
Cheol-Soo Park

Department of Architecture and Architectural Engineering
College of Engineering, Seoul National University
1, Gwanak-ro, Gwankak-gu
Seoul, 08826, SOUTH KOREA

Eiji Urabe
Jeonghun Gwak
Yongsung Park

High-Tech ENG Team,
Samsung C&T Corp.
26, Sangil-ro 6-gil, Gangdong-gu
Seoul, 05288, SOUTH KOREA

ABSTRACT

This paper reports a hybrid Gaussian process (GP) model of a chiller system developed with both the manufacturer's and operation data. The authors collected actual operation data of the chiller in an existing building at the sampling time of five seconds during two months. It is presented that the GP model based on both manufacturer's specification data and operation data performs far better than a manufacturer's data model or an operation data model.

1 INTRODUCTION

Chiller's performance is evaluated in terms of a ratio of removed heat to energy input called *coefficient of performance(COP)*. Chiller's manufacturers usually offer a COP data-sheet measured through a series of experimental tests under specific design conditions. However, in an actual operation, operational parameters such as temperatures and volume flow rates of cooling water and chilled water are different from the design condition, which can cause a performance gap between COP rated by manufacturer's data and actual COP. Hence, it is required for building facility managers to develop an appropriate COP model to determine optimal operation of cooling systems in an existing building. In this study, a data-driven modeling approach for a water cooling centrifugal chiller is proposed using both manufacturer's specification data and operation log data.

2 METHODOLOGY

Gaussian process(GP), one of the supervised learning methods, was adopted. GP estimates not individual outputs but a multivariate gaussian function with a mean function ($\mu: x \rightarrow R$) and a covariance matrix (kernel function: $K(x, x')$), so every x in input space can be probabilistically estimated. In this study, the gaussian-form radial basis function (RBF) was used because it can find a smooth function (Bishop, 2006).

$$\mathrm{K_{rbf}}(x, x') = \sigma^2 \exp\left(-\frac{(x-x')^2}{2l^2}\right) \tag{1}$$

The capacity of the target chiller is 2,500 USRT, and its rated COP_R is 7.129 under the following operating condition: cooling water (entering: 32℃, leaving: 37℃, flow rate: 478.8 l/s) and chilled water (entering: 17℃, leaving: 12℃, flow rate 420.6 l/s). The manufacturer's COP test data covers discretized condenser entering water temperatures (8 steps) and part load ratios (PLR, 10 steps) (8 × 10 = 80 data points). On the other side, the operation COP was calculated using collected data from July 01 to August

31 at the sampling time of five seconds including entering and leaving chilled water temperatures, chilled water flow rate, and energy use (a total of 17,560 data points). In this study, the GP model is first developed only with manufacturer's data because it covers a wide range of the input space. Then, the operation data is sampled and gradually appended to the training data-set to find an optimal combinations of data-set (Figure 1).

3 RESULTS AND CONCLUSION

Figure 1(a)-(b) shows the 3D COP contours based on the chiller's specification data and operation data. Figure 1(a) shows the chiller's COP under the laboratory's experimental condition, while Figure 1(b) reveals the actual operation but limited to very narrow input space. Thus, if we extrapolate the 3D contour in Figure 12(b) to a region of high PLR and low condenser entering temperature, it would predict biased performance, its COP's becoming close to 20.0. This is why the authors combined both the specification data and operation data as shown in Figure 1(c). The COP contour presented in in Figure 1(c) depicts more realistic performance of the actual chiller than Figure 1(a)-(b). In other words, the GP model developed with combined data could balance the prediction space between the specification and operation data of the chiller. The developed GP model in Figure 1(C) can be used for selecting optimal operational condition such as chilled water leaving temperature, cooling water entering temperature, etc. Rather than using a specification data-based model, it is suggested that a hybrid data-driven model out of the design and operation data can be effectively employed for daily practice of building operation.

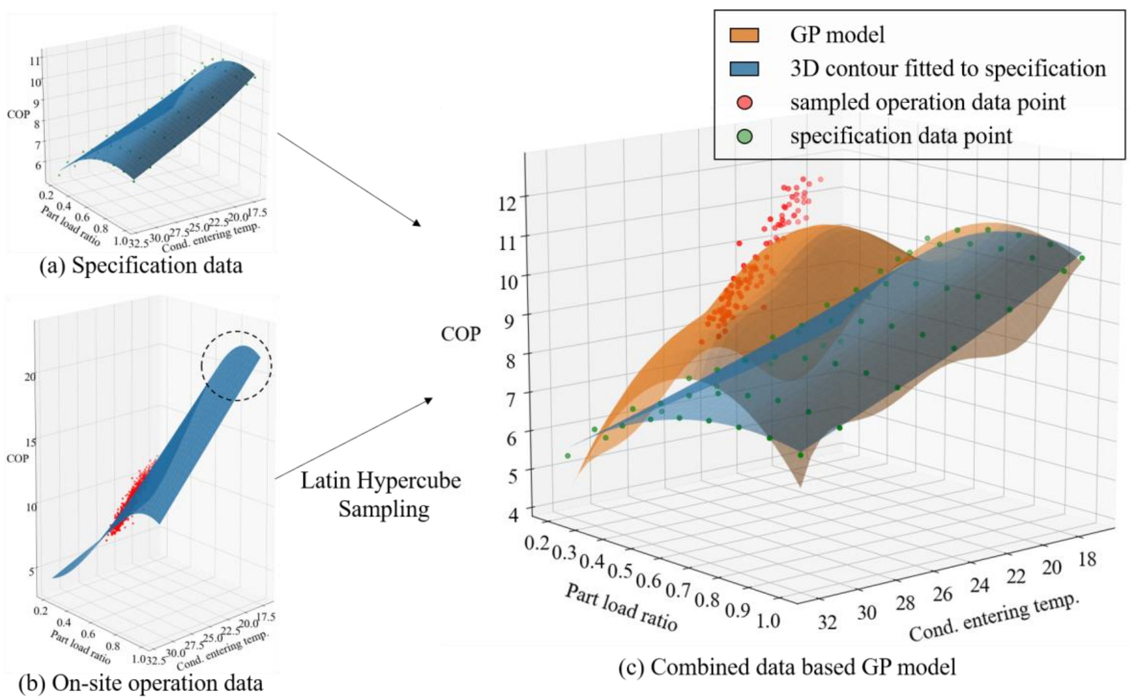

Fig. 1. Gaussian process model with combined data set.

ACKNOWLEDGEMENTS

This research was sponsored by the Samsung C&T research grant program

REFERENCES

Bishop C. M. 2006. *Pattern Recognition and Machine Learning*. New York: Springer.