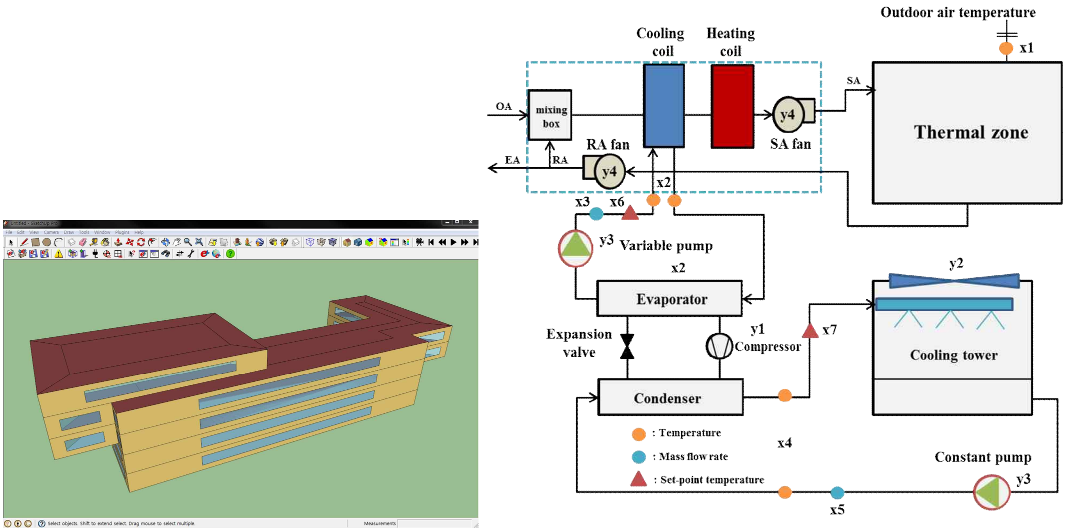


Figure 1. *EnergyPlus model and dataset collected from the chiller system (noted as x* and y*)*

The input dataset consist of outdoor air temperature (*x1*), differences in temperatures between supply and outlet of the chilled water loop and cooling water loop (*x2*, *x4*), mass flow rates of the chilled water loop and cooling water loop (*x3*, *x5*), outlet temperatures of chilled water loop and cooling tower loop (*x6*, *x7*). The output dataset consist of electric energy consumption of the chiller (*y1*), fan energy consumption of the cooling tower (*y2*), pump energy consumption (*y3*), and fan energy consumption of the AHU (*y4*). The dataset were collected with 1 hour interval from 2th August to 6th August for the GPM and from 9th August to 13th August for real-time NMPC respectively. In general, it is noteworthy that with a small quantity of the dataset, the GPM can be developed to predict dynamic behavior of the nonlinear system, compared to the other inverse models (Rasmussen 2004).

OPTIMAL CONTROL OF CHILLER SYSTEM

The control variables for the chiller operation are set-point outlet temperatures of chilled water loop (T_{chws}) and cooling tower loop (T_{ctws}). Equations 1-2 show a cost function and an optimization problem, respectively.

$$J_{cooling} = \int_{t_1}^{t_2} (Q_{chiller} + Q_{tower} + Q_{pump} + Q_{fan})dt \tag{1}$$

$$\begin{aligned} &MIN \ \ J_{cooling} = f(T_{chws}, T_{ctws}) \\ &s.t. \ \ 5℃ \le T_{chws} \le 13℃ \\ &\quad\ \ 28℃ \le T_{ctws} \le 32℃ \\ &\quad\ \ Var[J_{cooling}] \le 1.1 \end{aligned} \tag{2}$$

where $Q_{chiller}$ is electric energy consumption of the chiller (*y1*), Q_{tower} is fan energy consumption of the cooling tower (*y2*), Q_{pump} is the pump energy consumption (*y3*), Q_{fan} is fan energy consumption of the AHU (*y4*), Var is the variance.

Figure 2 shows a coupling between the GPM and Genetic Algorithm (GA) in MATLAB optimization toolbox. The GA is a random search technique that mimics the process of natural evolution for generating global solutions. In the GA process, initial populations for an optimization problem evolve toward better solutions through selection, crossover, and mutation. The process continuously iterates until reaching either satisfactory fitness level or the maximum number of generations.

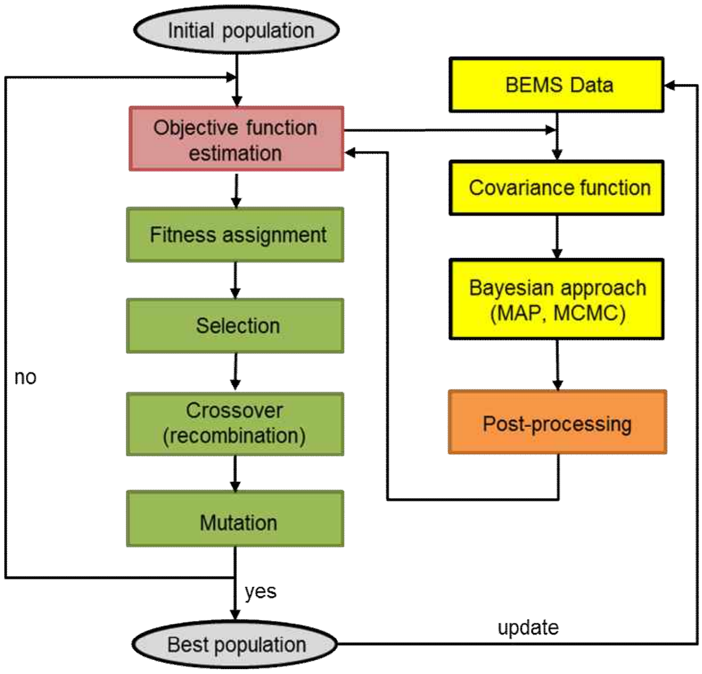


Figure 2. *Integration of the Genetic Algorithm to Gaussian Process Model*

In the paper, the number of initial populations and generations were set to 200 and 1000, respectively. The GA process with the GPM produces optimal control variables (T_{chws}, T_{ctws}) over each time horizon (1 hour), and then the control variables were used as inputs to EnergyPlus simulation run.

For validation's purpose, the GPM were compared to EnergPlus output using Mean Bias Error (MBE) and Coefficient of Variance of the Root Mean Square Error (CVRMSE) according to ASHRAE Guideline 14 (2002) (Table 1). The prediction of GPM is significantly close to that of EnergPlus. The prediction of GPM improves in terms of MBE and CVRMSE as time goes by. In case of August 12, there was a slight change in the pattern of outdoor air temperature, thus leading to increase in CVRMSE. However, after August 12, the GPM performs better since the time-series dataset were reflected in the model (Figure 2).

Table 1. *Comparison between EnergyPlus and GPM*

	August 9	August 10	August 11	August 12	August 13	Total
MBE (%)	3.85	0.46	2.11	-0.25	1.48	1.78
CVRMSE (%)	22.84	11.70	4.70	11.38	3.83	14.02

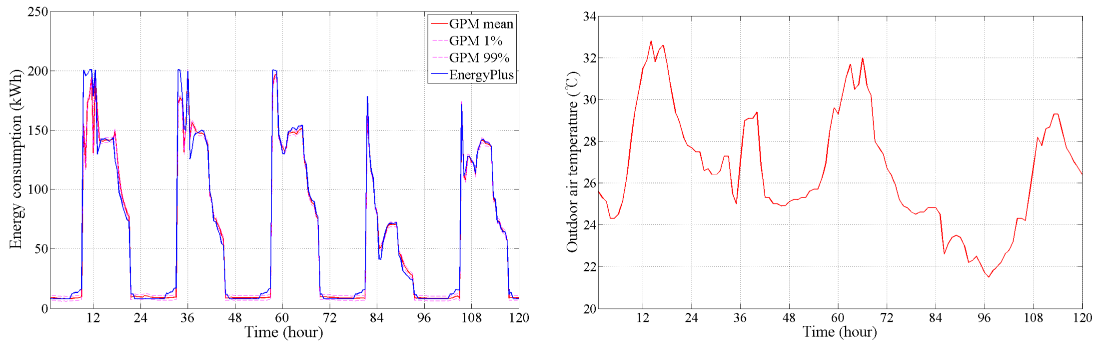
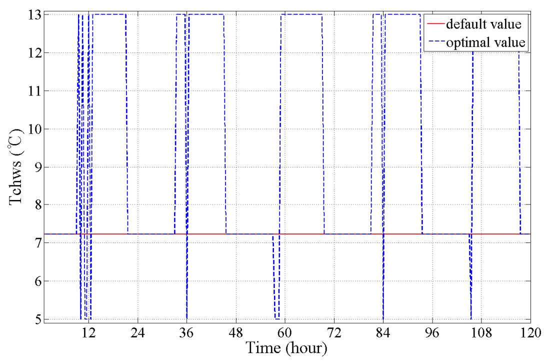
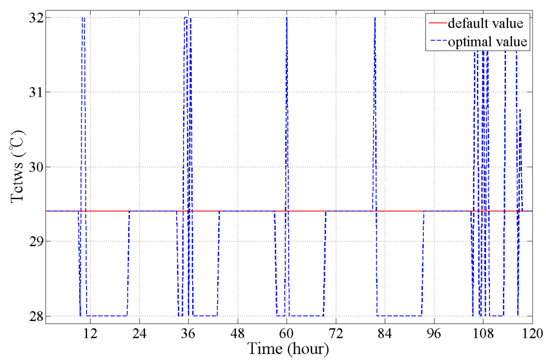


Figure 3. *Validation of GPM (left) and outdoor air temperature (right)*

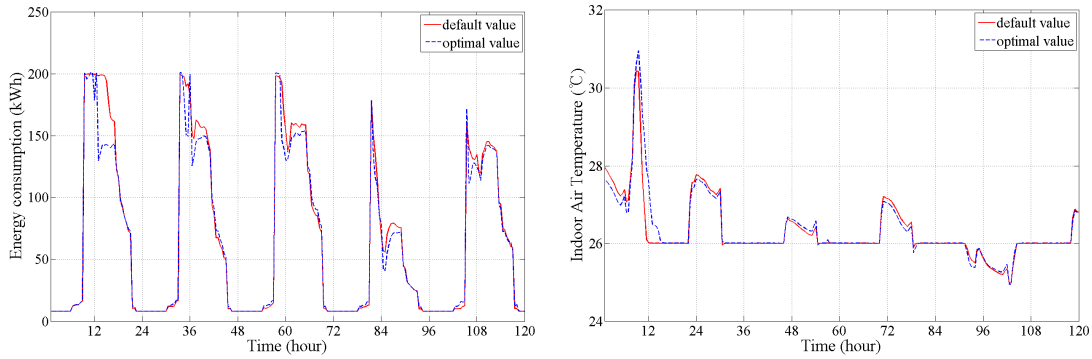
Figure 4 shows optimal T_{chws} and T_{ctws}, cooling energy consumption ($J_{cooling}$ in Equation (1)) and indoor air temperature. In Figure 4(a), default variables of T_{chws} (7.22°C), and T_{ctws} (29.4°C) were shown. As shown in Figures 4 (a)-(b), optimal T_{chws} and T_{ctws} were close to 13°C and 28°C, respectively during most of the operation period, in order to reduce the chiller electric energy consumption. The greater T_{chws}, the less energy consumption is. Please be noted that the reduction of the chiller electric energy consumption increases energy consumptions of the other cost elements (e.g. AHU fan, pump). However, the chiller energy consumption is more dominant than the others. Figure 4(c) shows comparison of energy consumption between default control and optimal control. Optimal control can reduce about 5 % of energy consumption compared to default control (Table 2). In terms of the indoor air temperature, optimal control can maintain a set-point of indoor air temperature (26°C) during the cooling period (from hour 9 to hour 21) as shown in Figure 4(d). In other words, the NMPC based on the GA and GPM performs better and can be readily available for stochastic control actions.



(a) T_{chws}



(b) T_{ctws}



(c) Cooling energy consumption (d) Indoor air temperature

Figure 4. *Optimal control results of chiller system*

Table 2. *Comparisons between EnergyPlus and GPM*

	Default control (kWh) (A)	Optimal control (kWh) (B)	Difference between A and B (kWh)	Saving (%)
August 9	4,021	3,614	408	11.28
August 10	3,455	3,318	138	4.14
August 11	3,622	3,514	109	3.10
August 12	1,927	1,813	114	6.27
August 13	3,010	2,942	68	2.31
Total	16,036	15,200	836	5.50

CONCLUSIONS AND FUTURE WORK

This paper addressed a stochastic NMPC using a coupling between GA and GPM for real-time chiller operation. The GPM produces accurate and reliable stochastic predictions and requires far less computation time, compared to the other system models. In particular, it has a surprising capability to approximately describe nonlinear behavior of the chiller system with the far less number of the training dataset. The real-time chiller operation with the stochastic NMPC provides optimal control variables (outlet temperatures of chilled water loop and cooling tower loop) over the time horizon, and training dataset are continuously updated for a high quality of the GPM. In other words, the GPM can be used to predict time-varying and nonlinear systems, leading to real time optimal control of any technical building system. Future works may include the following:

- Data filtering: In this study, the authors used EnergyPlus outputs in lieu of measured BEMS data. In general, the measured data may include numerous disturbances such as sensor errors. Future work will employ data filtering technique to improve reliability of the GPM and NMPC.

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