Nonlinear Predictive Control of Chiller System using Gaussian Process Model

Y.J. Kim¹, and C.S. Park²*

¹ Division of Architecture, Architectural Engineering and Civil Engineering, College of Engineering, Sunmoon University, Asan, Chungnam, 336-708, South Korea
² School of Civil and Architecture Engineering, College of Engineering, SungKyungKwan University, Suwon, Gyeonggi, 440-746, South Korea

ABSTRACT
For Nonlinear Model Predictive Control (NMPC) to be implemented in real application, data driven models are advantageous since they can be easily constructed and are relatively fast, compared to first principle based models (simplified calculation [ISO 13790], dynamic simulation [EnergyPlus, ESP-r, TRNSYS, etc.], state space models, etc.). Gaussian Process Model (GPM), one of the data-driven approaches, can be beneficially used for real time stochastic optimal control of nonlinear building systems, since the GPM is very lightweight in terms of computation time and does not require significant modeling efforts. The GPM is a black-box model based on Bayesian approach. For real-time optimal control of chiller operation in an office building, the authors developed a coupling between the GPM and an optimization routine (Genetic Algorithm) in MATLAB optimization toolbox. The two control parameters are studied in the paper: outlet temperatures of a chilled water loop as well as a cooling tower loop respectively. This study delivers real-time optimal outlet temperatures of the chilled water loop and cooling tower loop. In addition, the characteristics of GPM for reliable NMPC were discussed in the paper. It was shown that GPM produces satisfactory control performance taking into account the probabilistic nature of the chiller system.

KEYWORDS
Nonlinear Model Predictive Control, Inverse model, Gaussian Process, Bayesian approach, Genetic Algorithm

INTRODUCTION
Building Energy Management System (BEMS) has been installed for energy performance predictions and optimal operations of various building systems. However, most real system operations with BEMS are still based on subjective judgments and
operators’ experience rather than making the best use of Model Predictive Control (MPC). One of the reasons is that it is difficult to accurately predict dynamic behavior of time-varying systems under uncertainty. To deal with this, the previous study (Kim et al. 2014) proposed sampling methods (e.g. Simple Random Sampling [SRS], Quasi-Random Sampling [QRS], Latin Hypercube Sampling [LHS], etc.) using Monte Carlo simulation. The sampling methods are used to describe stochastic characteristics of energy systems’ behavior by generating a set of unknown inputs, but it takes vast computation time and simulation efforts. With this in mind, MPC integrated to BEMS is not easily implementable in terms of accuracy, reproducibility, reliability, and objectivity of performance predictions.

To solve the issues of uncertainty and computation time, this paper addresses real-time optimal chiller operation based on a coupling between an inverse model using Gaussian Process Model (GPM) and BEMS. The GPM is a kind of data driven inverse models and can be regarded as a black-box approach. It can predict dynamic behavior of nonlinear and time-varying systems and be used for stochastic NMPC. In particular, it requires significantly less computation time than the whole-building simulators (EnergyPlus, TRNSYS, ESP-r, etc.). In this study, an example of NMPC based on GPM is presented for a chiller operation.

**MODEL PREDICTIVE CONTROL AND SYSTEM MODEL**

Building systems are a set of transient objects which interact with many nonlinear systems, e.g. HVAC, chillers, boilers, pumps, fans, blinds, lights, etc. Due to transient and nonlinear nature, simple controllers (e.g. on/off control, P/PI/PID, etc.) are not enough to predict future states of the systems. In general, MPC consists of a system model, a cost function, constraints, and an optimization algorithm, and can be used for anticipatory performance prediction and control actions over the time horizon (Afram and Janabi-Sharifi 2014).

For a reliable MPC implementation, the system model must be carefully chosen, which can be classified as follows: (1) simplified energy calculation, (2) dynamic simulation, (3) lumped simulation model, and (4) data driven inverse model

- **Simplified energy calculation**: This approach is based on a set of simple algebraic equations and provides transparent and normative calculations. The ISO 13790 is typical. The simplified approach (ISO 13790) has several advantages, including (1) relatively less number of inputs, (2) transparent calculation rules, and (3) intuitive and easy identification of correlation between inputs and outputs. Due to these advantages, the simplified approach is suitable for energy performance prediction and energy retrofit analysis when fast calculation and rapid decision making are required. However, the simplified approach is not good enough to describe complex nonlinear dynamics of systems and corresponding control actions.
Dynamic simulation: Whole building dynamic simulators can describe transient and nonlinear nature of building systems with a high level of modeling capability. In particular, dynamic simulations have been used for real time building control using middleware programs (MLE+, BCVTB, FMU, etc.) (Wetter 2011; Bernal et al. 2012; Nouidui et al. 2014). However, dynamic simulations require excessively many inputs, and simulationists must be very knowledgeable and have good hands-on experience. These issues cause the model uncertainty, and it is not easy to estimate unknown inputs. As a remedy for this, an on-line self-calibration and optimal control has been proposed (Yoon et al. 2011).

Lumped simulation model: The lumped simulation model is usually expressed in state space equations. In general, a local system is modelled, and then optimal control is applied. The local system, a part of any building system, can be predicted with far less modeling efforts and computation time since the model deals with only a small part of the building. However, it should be noted that the model can’t represent the whole building and building systems have strong interdependency.

Data driven inverse model: The inverse model employs a black-box approach using measured data and stochastic techniques. The inverse models comprise regression models, Artificial Neural Network (ANN), Support Vector Machine (SVM), and Gaussian Process Model (GPM) (Zhang et al. 2013). The GPM provides probabilistic outputs, unlike the others. In other words, the GPM has a capability for stochastic performance predictions. The GPM is based on a regression model with Gaussian noise using a training dataset, Gaussian Process, and Bayesian inference. The Gaussian process consists of the mean function and the kernel matrix composed of covariance function. The unknown parameters such as scale parameter, length-scale parameter, and error parameter in the regression model were estimated by a Maximum A Posteriori (MAP) approach, one of Bayesian inference methods. Since the GPM can reflect the model uncertainty, it can be successfully used for NMPC (Rasmussen and Williams 2006).

TARGET BUILDING AND SYSTEM

Due to lack of the measured data, EnergyPlus was used to imitate a 5-storey office building as shown in Figure 1. It was assumed that mass flow rates, temperatures and energy consumptions are measured in BEMS. The HVAC systems and plants are as follows: 5 Variable Air Volumes (VAVs), 20 Fan Coil Units (FCUs), 1 centrifugal chiller, 1 boiler, and 3 pumps. In EnergyPlus, default values of simulation inputs (heat balance algorithm, constructions, windows, indoor loads, infiltration rates, thermal properties of HVAC and plants, control logics, etc.) were used (ASHRAE 2013). Figure 1 shows inputs (denoted as \( x^* \)) and outputs (denoted \( y^* \)) for GPM.
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 2\textsuperscript{nd} August to 6\textsuperscript{th} August for the GPM and from 9\textsuperscript{th} August to 13\textsuperscript{th} 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.

$$J_{\text{cooling}} = \int_{t_0}^{t_f} (Q_{\text{chiller}} + Q_{\text{tower}} + Q_{\text{pump}} + Q_{\text{fan}}) dt$$  

$$\text{MIN } J_{\text{cooling}} = f(T_{chws}, T_{ctws})$$  
\hspace{1cm} s.t. \ 5^\circ C \leq T_{chws} \leq 13^\circ C$$  
\hspace{1cm} \ 28^\circ C \leq T_{ctws} \leq 32^\circ C$$  
\hspace{1cm} \text{Var}[J_{\text{cooling}}] \leq 1.1$$

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

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 \((T_{\text{chws}}, T_{\text{ctws}})\) 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 EnergyPlus 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 EnergyPlus. 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

<table>
<thead>
<tr>
<th></th>
<th>August 9</th>
<th>August 10</th>
<th>August 11</th>
<th>August 12</th>
<th>August 13</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>MBE (%)</td>
<td>3.85</td>
<td>0.46</td>
<td>2.11</td>
<td>-0.25</td>
<td>1.48</td>
<td>1.78</td>
</tr>
<tr>
<td>CVRMSE (%)</td>
<td>22.84</td>
<td>11.70</td>
<td>4.70</td>
<td>11.38</td>
<td>3.83</td>
<td>14.02</td>
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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.
(c) Cooling energy consumption  (d) Indoor air temperature

**Figure 4. Optimal control results of chiller system**

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

**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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