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Comparative study of surrogate models for uncertainty quantification of building energy model: Gaussian Process Emulator vs. Polynomial Chaos Expansion

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ABSTRACT

Uncertainty Quantification (UQ) employing a Monte Carlo Sampling (MCS) method in a building simulation domain has been widely used to account for risks of predicted outputs for robust decision making. However, the stochastic approach for UQ problems requires significant computational burdens compared to the deterministic approach. This paper addresses two surrogate models (Gaussian Process Emulator (GPE) and Polynomial Chaos Expansion (PCE)) which together can be regarded as a meta-model of a Building Performance Simulation (BPS) tool with a high-fidelity model. In the paper, the developed GPE and PCE with different model structures were compared in terms of a prediction capability under different amount of training data and number of inputs. The aim of the comparative study is to identify the relative prediction abilities and model flexibility of GPE and PCE. It was found that the GPE and PCE produce high performance qualities having fast computation speed compared to the developed basis model if new inputs having identical inputs and probability ranges were used. In terms of two-sample Kolmogorov-Smirnov (K-S) hypothesis test, mean values of the minimum p-values of the GPE and PCE were 0.999 and 0.569, respectively, if the number of samplings are over 30 cases. Otherwise, the PCE shows significantly reduced performance quality than the GPE.

1. Introduction

Recently, Building Performance Simulation (BPS) tools have been widely used for performance assessments of various systems due to their attractive abilities for treating energy and mass flows in building environments. Utilizing the abilities of these BPS tools, effective answers can be found regarding the various real problems encountered in building environments from design process to operation process. However, approximate modeling levels would be needed for simulationists to determine definite values for deriving a simulation domain from a real building domain. The simulation confirms the definite values in a given building simulation environment are not easy as it thinks even if the simulationists combine a distinguished talent. This is because the BPS tools have been embedded into various uncertainty sources such as modeling uncertainty, numerical uncertainty, scenario uncertainty, and specification uncertainty. However, if the simulationists ignore such uncertainty sources, the predicted outputs might provide meaningless information due to performance gaps compared with the reality. To deal with the aforementioned issue, an uncertainty analysis based on a stochastic approach has been used to identify the risks embedded in the simulation domain. This will help to unveil the problems hidden within the simulation domain based on deterministic methods.

Considering the uncertainty analysis, a previous studies [1] were presented based on the International Building Performance Simulation Association (IBPSA) (www.ibpsa.org), following the PhD theses of de Wit [2] and Macdonald [3]. In this respect, building experts have been started to recognize that the performance predictions of the BPS tools are not deterministic, but stochastic. Nevertheless, some building experts still believe that the predicted outputs of the BPS tools can be used, without considering the uncertainty sources as undeniably accurate decision making information for solving real problems. This is partly because the increased computational burdens of the BPS tools for the uncertainty propagation act as a significant obstacle to adopting the stochastic approach, considering the limited time and budget in reality.

Previous studies [4–7] have proposed surrogate models for alleviating these computational burdens in the engineering decision

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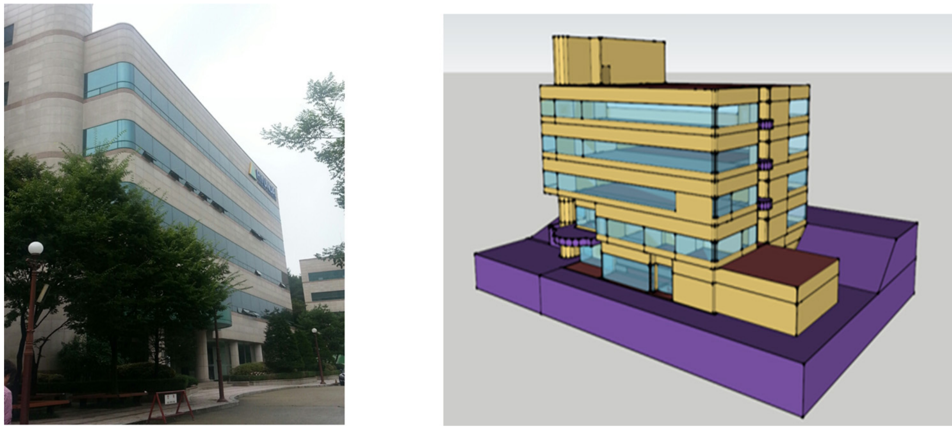

Fig. 1. Target building (left) and EnergyPlus displayed in OpenStudio (right).

making process. The Gaussian Process Emulator (GPE) and Polynomial Chaos Expansion (PCE) in the surrogate models have been most widely used and continuously developed in applied mathematical and statistical communities [4]. The GPE and PCE have also been used for drawing meaningful and trustworthy probabilistic predictions considering expensive natures of complex BPS tools (e.g. EnergyPlus) in the building simulation domain. The abilities of GPE and PCE for reliable performance assessments under

Table 1
Calibrated unknown inputs (N: Normal distribution, T: Triangular distribution, D: Definite value).

Classification		Descriptions		Calibrated input values
	x1	Concrete	Density (kg/m^3)	N[2247.82, 140.6]
	x2		Specific heat (J/kg-K)	N[937.28, 75.3]
	x3		Conductivity (W/m-K)	N[1.4958, 0.24]
	x4		Density (kg/m^3)	N[1805.25, 105.9]
	x5	Mortar	Specific heat (J/kg-K)	N[856,91]
	x6		Conductivity (W/m-K)	N[0.914, 0.34]
	x7		Density (kg/m^3)	N[1925,189]
	x8	Concrete block	Specific heat (J/kg-K)	N[840,90]
	x9		Conductivity (W/m-K)	N[0.922, 0.24]
	x10		Density (kg/m^3)	N[2545,323]
	x11	Stone	Specific heat (J/kg-K)	N[829,162]
	x12		Conductivity (W/m-K)	N[2.536, 0.86]
Construction materials	x13		Density (kg/m^3)	N[38,27]
	x14	Insulation	Specific heat (J/kg-K)	N[1072,298]
	x15		Conductivity (W/m-K)	N[0.0412, 0.01]
	x16		Density (kg/m^3)	N[2146,266]
	x17	Waterproof Asphalt	Specific heat (J/kg-K)	N[1232,431]
	x18		Conductivity (W/m-K)	N[1.050, 0.31]
	x19		Density (kg/m^3)	N[709.68, 287.1]
	x20	Board	Specific heat (J/kg-K)	N[1561.32, 559.4]
	x21		Conductivity (W/m-K)	N[0.191, 0.15]
	x22	Window #1	U-factor (W/m^2-K)	N[3.2881, 0.31]
	x23		SHGC (dimensionless)	N[0.4306, 0.04]
	x24	Window #2	U-factor (W/m^2-K)	N[5.657, 0.57]
	x25		SHGC (dimensionless)	N[0.765, 0.08]
	x26	Infiltration	Air Change per Hour (1/h)	N[0.3279, 0.01]
Indoor loads	x27	Light	Fraction internal gain	N[0.8322, 0.09]
	x28	Equipment	Fraction internal gain	N[0.7218, 0.05]
	x29		Fan Efficiency	N[0.7, 0.07]
	x30	Supply fan	Pressure Rise (Pa)	N[598.51, 4.99]
HVAC	x31		Motor Efficiency	T[0.5, 0.9, 0.95]
	x32		Fan Efficiency	N[0.7, 0.07]
	x33	Return fan	Pressure Rise (Pa)	N[600.28, 5.01]
	x34		Motor Efficiency	T[0.5, 0.9, 0.95]
	x35	Chilled water pump	Rated Pump Head (Pa)	N[19951.09, 386.39]
	x36		Motor Efficiency	T[0.5, 0.9, 0.95]
Pump	x37	Condenser pump	Rated Pump Head (Pa)	N[20031.04, 384.04]
	x38		Motor Efficiency	T[0.5, 0.9, 0.95]
	x39	Hot water pump	Rated Pump Head (Pa)	T[170000,180000, 190000]
	x40		Motor Efficiency	T[0.5, 0.9, 0.95]
Plant	x41	Absorption	Fuel Input to Heating Output Ratio	N[1.5, 0.15]
	x42	Chiller/Heater #1	Fuel Input to Cooling Output Ratio	N[0.873, 0.0624]
	x43	Absorption	Fuel Input to Heating Output Ratio	N[1.5, 0.15]
	x44	Chiller/Heater #1	Fuel Input to Cooling Output Ratio	N[0.980, 0.0937]
	x45		Prediction error	D[1.0]
Future climate data	x46	SRA1B scenario	Spatial downscaling error	D[1.0]
	x47		Temporal downscaling error	D[1.0]