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Multi-Criterion Optimal Design of Building Simulation Model using Chaos Particle Swarm Optimization

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Abstract. This paper addresses a multi-criterion optimal design problem under uncertainty for obtaining a high level of robust design decision making during early design process. Building Performance Simulation (BPS) tools have computation capacities for handling dynamic and nonlinear behaviors in realistic systems and integrating an optimization routine for finding a global solution. However, a multi-criterion optimal design using BPS tools for rapid and proper design exploration has some limitations as follows: (1) model uncertainty, (2) weighting problem in a cost function, (3) high computational effort, and (4) being trapped in local optima. In this study, the aforementioned optimization problems were solved using a Gaussian Process (GP) emulator and Chaos Particle Swarm Optimization (CPSO). It has been elaborated in the study that CPSO approach is superior to traditional Particle Swarm Optimization (PSO) in terms of searching for global optima.

Keywords: Multi-criterion optimal design, Uncertainty, Gaussian Process emulator, Chaos theory, Particle Swarm Optimization

1 Introduction

An optimal design using Building Performance Simulation (BPS) tools is widely used to achieve a performance goal reflecting preferences for multi-decision makers. The BPS tools can describe a complex physical phenomenon through mathematical rules. In particular, coupling between BPS tools and optimization techniques is possible to solve a high degree of optimization problem. In spite of these academic growths, a decision making in the reality is relying on subjective judgments of a few decision makers. Among those reasons, only the issues in an uncertainty and optimal design exploration could be listed as follows: (1) model uncertainty, (2) weighting problem in a cost function, (3) high computational effort, and (4) being trapped in local optima.

To solve the aforementioned issues, this study addresses an optimization algorithm using chaos theory. For this study, a Gaussian Process (GP) emulator was employed to produce reliable probabilistic outputs having fast calculation speed compared to the whole-building simulation tools [1-2]. And we used PSO using a random generator

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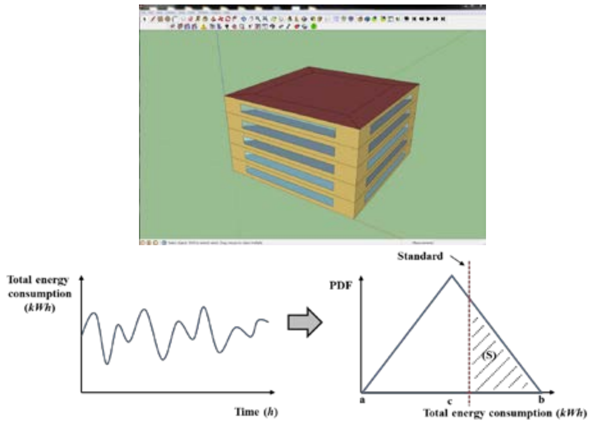
based on a chaos theory [3-5]. In other words, this study addresses a framework to deal with the stochastic multi-criterion optimization problems throughout coupling between Chaos PSO (CPSO) and the GP emulator.

2 Stochastic multi-criterion optimal design using Chaos theory

Monte Carlo (MC) simulation treats propagation of the uncertainty that executes iteratively simulation runs, but it is a time-consuming work. In this context, the stochastic approach can hand over meaningful information for solving the optimization problems, if it could be possible to have fast calculation speed. In the study, a GP emulator is used for a stochastic optimal design instead of BPS tools. Since the GP emulator is a helpful for producing reliable probabilistic prediction outputs with less computation burden. And the optimal design generally involves multi-criterion having different weights among cost function elements, not single-criterion. For reflecting the desired pay-off between criteria, the progressive preference articulation was employed. The population-based evolutionary algorithms attempt to search global optima using a random search technique. In the algorithms, the random search technique was employed for generating random numbers throughout a uniform probability distribution on the interval [0, 1]. It is important to diversify populations of the design variables and avoid the premature convergence during the optimal design exploration. To solve the problem, this study used random numbers generated by chaos sequences.

3 Target building & optimal results

An exemplified office building was selected for this study as shown in Fig. 1(a). EnergyPlus 8.0 was chosen as a BPS tool. Total energy consumption (*kWh*) and Predicted Mean Vote (PMV) (*dimensionless*) were chosen as the predicted outputs. For the multi-criterion optimal design, it is important that each cost function element must all be of equal units to transfer into single cost function. In the study, each cost function element was represented by a triangular probability distribution, and it then was changed to the cumulative probability exceeding the preferred criteria by decision makers as shown in Fig. 1(b). The preferred criteria of total energy consumption and PMV were set to 400 (*kWh*) and 0.8 (*dimensionless*), respectively. With in/output training dataset in which EnergyPlus is iteratively executed according to the input samples propagated by LHS method, the GP emulator can build a stochastic regression model with a Gaussian noise.



(a) EnergyPlus model (b) Change of the predicted output

Fig. 1. Simulation model and change of the cost function using the probability distribution

The design variables selected 18 walls, 14 roofs, 418,161,601 windows # 1-4 per orientation (= 143 [north window] × 143 [west window] × 143 [east window] × 143 [south window], 81 blinds # 1-4 per orientation (= 3 [north window] × 3 [west window] × 3 [east window] × 3 [south window]). The cost function elements are cumulative probabilities of total energy consumption and PMV exceeding the preferred conditions as shown in Eq. 1.

$$MIN\ F(X) = w_1 \times E[f_1] + w_2 \times E[f_2] \tag{1}$$
$$s.t.\quad Var[f_1]^2 / E[f_1] \le 1.0$$
$$Var[f_2]^2 / E[f_2] \le 1.0$$

where, w_1, w_2 are weights, f_1 is a cumulative probability of total energy consumption exceeding the preferred condition, f_2 is a cumulative probability of PMV exceeding the preferred condition, *Var* is a variance, *E* is an expected or mean value.

Table 1 shows stochastic fitness results and mean computation time regarding with total energy consumption, PMV, and cost function.

Table 1. Fitness results and mean computation time of cost function (PSO vs. CPSO)

Methods		PSO	CPSO				
			Circle	Gauss	Logistic	Piecewise	Tent
Total energy consumption	Min	0.20537	0.20384	0.20600	0.20557	0.20328	0.20528
	Max	0.21297	0.21338	0.21236	0.21367	0.21453	0.20913
	Mean	0.20931	0.20961	0.20908	0.20927	0.20929	0.20687
	Standard deviation	0.00277	0.00298	0.00210	0.00288	0.00385	0.00118
	Coefficient of variation	0.01325	0.01424	0.01004	0.01374	0.01840	0.00571

PMV	Min	0.72870	0.72734	0.72734	0.72598	0.72515	0.72968
	Max	0.73399	0.73286	0.73302	0.73406	0.73286	0.73152
	Mean	0.73124	0.73032	0.73013	0.73014	0.72949	0.73107
	Standard deviation	0.00138	0.00158	0.00163	0.00225	0.00288	0.00052
	Coefficient of variation	0.00189	0.00217	0.00224	0.00308	0.00395	0.00072
Cost function	Min	0.46902	0.46791	0.46851	0.46843	0.46799	0.46808
	Max	0.47164	0.47170	0.47046	0.47140	0.47077	0.47008
	Mean	0.47028	0.46997	0.46961	0.46971	0.46939	0.46897
	Standard Deviation	0.00093	0.00120	0.00058	0.00075	0.00080	0.00054
	Coefficient of variation	0.00199	0.00255	0.00124	0.00160	0.00170	0.00115
	Mean computation time	1hour 33minute	2hour 11minute	1hour 57minute	1hour 42minute	1hour 59minute	2hour 29minute

In the results, CPSO is superior to PSO in the given optimal design. It means that the stochastic multi-criterion optimal design can obtain a high quality of optimal solutions in which random numbers were generated by chaos maps instead of previous random numbers using the uniform probability distribution even though PSO spends less mean computation time than CPSO. In particular, a tent map in CPSO has less a coefficient of variation than the others. In other words, the tent map has high possible to avoid a premature convergence such as being trapped local minima.

4 Conclusions and Future works

This paper presented a cast study for dealing with the problems such as uncertainty, multi-criterion, high computation time, and premature convergence incurred from the stochastic multi-criterion optimal design using the BPS tools during early design process. For the case study, the optimal solutions were drawn into a framework throughout coupling between CPSO and the GP emulator. In the multi-criterion process based on the progressive preference articulation approach, the GP emulator is a helpful meta-model or surrogate model of the EnergyPlus since it should provide reliable probabilistic predicted outputs with fast computation speed comparing those of the EneryPlus. Furthermore, CPSO was introduced to avoid the premature convergence in PSO by generating pseudo random numbers based on chaos behaviors using various chaos maps (circle, gauss, logistic, piecewise, and tent, etc.). As a result, the chaos behaviors with ergodicity can draw a meaningful optimal solution by extracting different random numbers in the input space. In particular, the tent map out of the introduced chaos maps has less risk than the others and should be sufficiently utilized to search the global optima in the given stochastic multi-criterion optimal design. Future works will investigate applicability as well as pros and cons of CPSO by coupling between CPSO and the GP emulator in various design problems.

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