Supplementary Material for Multi-Objective Optimization for Flexible Building Space Usage

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I. Introduction

This supplementary material is to provide additional resources linked to the paper *Multi-Objective Optimization for Flexible Building Space Usage*. The document allow for further understanding of this paper and the results.

II. Comparison of XGBoost, Neural Network and Linear Regression

We list the detailed comparison of three regression algorithms which are linear regression (LR) [1], neural network (NN) [2] and XGBoost [3] here. LR is the simplest version of linear regression. NN and XGBoost are fine-tuning by Optuna [4]. The best hyper-parameters of NN are as follows: for the model of offices, num_layers is 4, num_units is 13 $learning\_rate$ is 0.004; for the model of meeting rooms, num_layers is 3, num_units is 4 $learning\_rate$ is 0.010. The Mean Squared Error (MSE) for those methods are shown in Table I.

TABLE I
Comparison of LR, NN and XGBoost

	LR	NN	XGBoost
MSE for the office model	0.210	0.190	0.135
MSE for the meeting room model	0.352	0.338	0.264

III. NSGA-II Parameters and EAF Plots

A. NSGA-II Parameters

We implement the original NSGA-II [5] and only use the mutation operator in this work. The NSGA-II parameters of both case study 1 and 2 are shown in Table II.

TABLE II
NSGA-II Parameters

	Population size	Mutation frequency	Number of iterations
Case 1	50	1	50
Case 2	50	1	80

B. Empirical Attainment Function Plots

The attainment function can describe the location of the distribution of a random non-dominated point set. The Empirical Attainment Function (EAF) is the function that can be estimated from experimental data via its empirical counterpart [6]. We repeat the experiments 40 times and the EAF plots for case study 1 and 2 are shown in Figure 1, 2. Our purpose is to reduce the randomness in NSGA-II and illustrate the "statistical distribution".

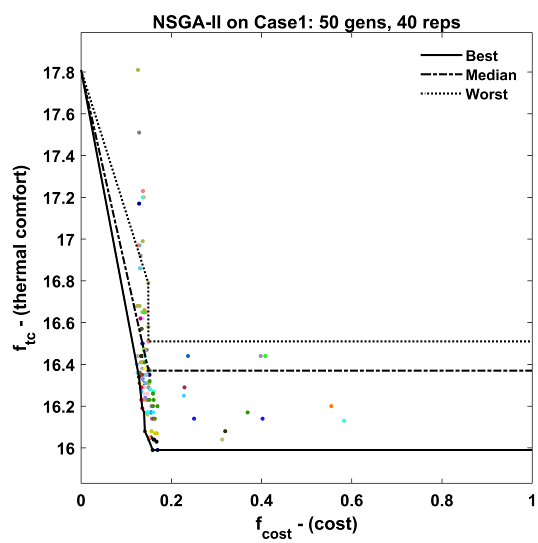

Fig. 1. Case study 1: EAF plot

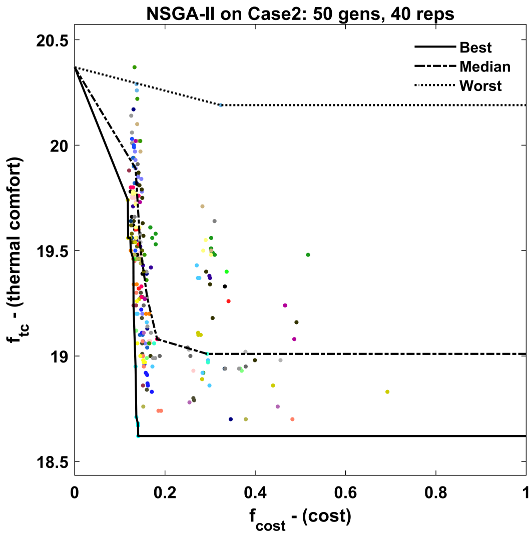

Fig. 2. Case study 2: EAF plot

References

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