OPTIMIZATION OF TIME-CONSUMING BUILDING PERFORMANCE OBJECTIVES

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***Abstract*—Buildings have multiple performance aspects that are usually conflictive (e.g., better buildings typically entail higher costs). These aspects require different simulation tools that perform extensive calculations. Because of this, multiple objective optimizations with metaheuristic algorithms have been widely used to solve building performance optimization problems. Alas, most of these tools and algorithms take significant time to correctly produce outputs and require extensive knowledge to interpret results. Ergo, building optimization with time-consuming simulation tools is often rendered unfeasible and requires a specific methodology to overcome these barriers. This work describes a standard pipeline of activities for multi-objective optimizations with time-consuming building simulations. Initially, a baseline Multi-objective optimization process is integrated with a widely used, validated building energy simulation tool. The goal is to minimize the energy use and cost of construction of a residential building complex composed of 6 buildings. Afterward, machine learning and optimization techniques are used to create a surrogate model capable of predicting simulation results much faster with adequate accuracy. Finally, different metaheuristics with their tuned hyperparameters are compared. Results show significant improvements in optimization results of up to a decrease of 22% of the total cost while having similar performance results and execution times up to 100 times faster.**

***Index Terms*—Building Optimization, Building simulation, Surrogate models, SDG7, SDG11, SDG13**

I. INTRODUCTION

With the current urbanization and population growth, along with climate change and all threats posed by carbon emissions and energy consumption, large efforts are being employed to mitigate these effects on a global scale. Particularly, the Architectural, Engineering, and Construction (AEC) industry is responsible for 40% of the world's energy consumption [28]. Thus, it is no surprise that performance-driven construction for more sustainable buildings is emerging as a significant field of research and a target for high political agendas [15].

Building Performance Simulation (BPS) and Optimization (BPO) have been integrated recurrently into the AEC industry. Particularly, commonly used Computer-Aided Drafting (CAD) tools have been integrating simulation tools and optimization algorithms in their toolset and workflows, allowing practitioners to experience a more efficient process, and make better-informed decisions [1], [2], [17], [18], [29].

BPO typically entails multiple objectives which are often conflictive [17]. Additionally, most building performance indicators are outputs of BPS, or extensive calculations performed by field experts [31]. Because of this, AEC optimization problems that are focused outside the practitioners' realm of knowledge are usually treated as Multi-Objective Optimization (MOO) problems with derivative-free functions [17], [19], [20], [29]. Metaheuristics, a class of optimization algorithms, have been widely used in the field of optimization for the AEC industry with positive results. These algorithms guide their search based on biological heuristics such as evolutionary, and swarms of different kinds, among others [32]. Furthermore, Wolpert and Macready state with the "No Free Lunch" theorem that no algorithm outperforms all others for all problems. This means that one has to either know from experience which algorithms yield better performances for each BPO problem or test multiple metaheuristics to find the best one [30]. Moreover, these algorithms have variables that define how they search for the optimal space called hyperparameters. These need to be fine-tuned to provide optimum results [4].

BPO functions that are outputs of BPS are significantly time-consuming [13], [22], [24], and when integrating them with the above-mentioned pipeline of activities for a derivative-free MOO problem, it usually renders the process unfeasible. Thus, emerging research in this field has been studying alternatives and approaches that allow us to overcome these barriers. Surrogate models have been used to work around these barriers successfully [3], [14], [27], [31] by significantly speeding up the time it takes to obtain BPS results.

This work structures previous research to illustrate the steps and processes required to perform a standard pipeline of activities for a BPO of time-consuming functions. Initially, a baseline MOO problem is integrated with a widely used metaheuristic and BPS tool. The obtained results are coupled with machine learning techniques and regression algorithms to generate a surrogate model capable of yielding significantly faster simulation results based on the BPO decision variables. With this surrogate model, it is feasible to finetune the metaheuristics hyperparameters, compare their performance for a specific BPO problem, and benchmark their results. This process is applied to a case study of a residential complex composed of 6 buildings in Lisbon, Portugal.

II. Methodology

The methodology for this work can be further subdivided into four sections: Baseline Optimization, Surrogate model, Hyperparameter Tuning, and Results and Discussion (Fig.1). In the Baseline Optimization section, the optimization objectives and decision variables are described, and a simulation-based optimization with EnergyPlus [10] in a Python environment [21] is integrated to compile a training database. This database is used in the Surrogate Model section to train a Convolutional Neural Network (CNN) with the Keras and TensorFlow packages [12] capable of predicting the total energy use of the 6 buildings and their standard deviation. The CNN layers' nodes are optimized with a Bayesian Optimization using Gaussian processes [25]. In the Hyperparameter Tuning section, four metaheuristics are selected to be compared. Each algorithm's hyperparameters are fine-tuned with a Bayesian Optimization as well. Finally, the metaheuristics are compared regarding their performance indicators, and optimization results are discussed for this particular class of BPO problem.

A. Baseline optimization

Our BPO problem is to find the best combination of constructions for each building's surface type that minimizes construction cost and total energy use. The case study comprises a standard Midrise apartment program from LadybugTools for building operation, usage, and schedules [23] applied to a geometric model of 6 buildings in Lisbon, Portugal, illustrated in Fig.2. Ladybug tools integrate the Rhino CAD tool with EnergyPlus by translating geometrical representations and weather files to a file folder and format that is readable by EnergyPlus. In this case study, a simulation of each building's total heating and cooling energy (J) is performed with an ideal Air Load system for one year with residential occupation schedules (Table I).

TABLE I
Simulation settings for the optimization

Period	1 year
Timestep	1 timestep per hour
Program	Midrise Apartment
Outputs	Zone Ideal Loads Supply Air Total Heating Energy (J) Zone Ideal Loads Supply Air Total Cooling Energy (J)

Each building can have one out of three different constructions for each surface type: exterior walls, interior floors, roofs, and windows. Thus, our optimization problem comprises the walls, roofs, floors, and windows of 6 buildings with a total of 24 variables with 3 possible constructions each (Table II). The opaque materials' properties are represented from their outermost layer to their innermost, and the window materials are defined using a simple glazing system definition with the window U-value, Solar (τ_{sol}), and Visible Transmittance (τ_{vis}). Each simulation takes $\approx$ 25 (s).

The optimization variables and goals are described in (1), (2), (3), and (4). (1) represents the total energy use of building n, (2) is the total energy use of all buildings, (3) is the standard deviation of the building sample, and (4) is the total cost of construction. The BPO problem objectives are to minimize these functions to guarantee the fairness of performance among buildings, minimum costs and energy uses. The Non-Dominated Sorting Genetic Algorithm (NSGAII) [9] was the chosen algorithm to run for 1000 iterations.

TABLE II
Materials for each surface type construction

	x	**Materials**			**Cost €/m2**
Walls	0	Plaster – 2cm Bored brick – 15 cm Air gap – 6 cm Bored brick – 11 cm Stucco – 1.5cm			25
	1	Plaster – 2cm Bored brick – 11 cm Air gap – 6 cm Bored brick – 11 cm Stucco – 1.5 cm			20
	2	Plaster – 2cm Bored brick – 15 cm Air gap – 6 cm XPS – 4 cm Bored brick – 11 cm Stucco – 1.5cm			35
Floors	0	Wood panels – 12 cm Stucco – 1.5 cm			10
	1	Ceramics – 1cm Screed – 8 cm Lightweight slab – 15 cm Stucco – 1.5 cm			25
	2	Ceramics – 1cm Screed – 8 cm Concrete slab – 15 cm Stucco – 1.5 cm			30
Roofs	0	Screed – 8 cm Waterproofing – 0.2 cm Screed – 8 cm Lightweight slab – 25 cm Stucco – 1.5 cm			20
	1	Screed – 8 cm Waterproofing – 0.2 cm XPS – 4 cm Screed – 8 cm Lightweight slab – 25 cm Stucco – 1.5 cm			30
	2	Screed – 8 cm Waterproofing – 0.2 cm XPS – 4 cm Screed – 8 cm Concrete slab – 15 cm Stucco – 1.5 cm			35
		UW/m^2K	τ_{sol}	τ_{vis}	
Windows	0	2.69	0.75	0.8	50
	1	1.70	0.38	0.7	80
	2	1.25	0.2	0.7	100

$$E_n(x_0,\ ...,\ x_{n\times4}) =\ Heating_n + Cooling_n\ kWh/m^2 \quad (1)$$

$$f_1\ \ (x_0,\ ...,\ x_{n\times4}) = \sum E_n\ (x_0,\ ...,\ x_{n\times4})\ kWh/m^2 \quad (2)$$

$$f_2\ \ (x_0,\ ...,\ x_{n\times4}) = \sigma(E_n(x_0,\ ...,\ x_{n\times4}))\ kWh/m^2 \quad (3)$$

$$f_3\ \ (x_0,\ ...,\ x_{n\times4}) = Cost(x_0,\ ...,\ x_{n\times4})\ € \quad (4)$$

$$x\ \in\ \{0,\ 1,\ 2\} - Number\ of\ construction\ types$$
$$n = Number\ of\ buildings$$

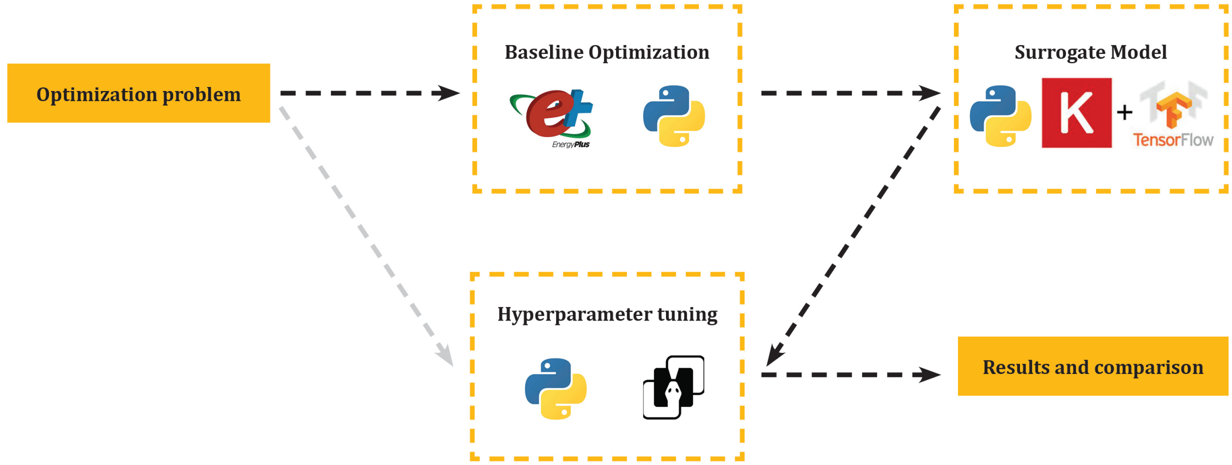

Fig. 1. Methodology Diagram

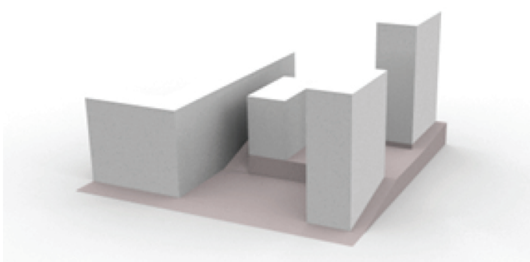

Fig. 2. Methodology Diagram

TABLE III
OPTIMUM CONVOLUTIONAL NEURAL NETWORK STRUCTURE AND PERFORMANCE FOR SURROGATE MODEL OF EQUATION (2).

Layer (Type)	**Filters**	**Kernel size**
Dense	300	1
1D-Convolutional	157	2
1D-Convolutional	6	2
1D-Convolutional	290	2
1D-Convolutional	70	1
Dense	1	1
R2 score	0.96	
RMSE (kWh/m2)	0.54	

TABLE IV
OPTIMUM CONVOLUTIONAL NEURAL NETWORK STRUCTURE AND PERFORMANCE FOR SURROGATE MODEL OF EQUATION (3).

Layer (Type)	**Filters**	**Kernel size**
Dense	300	1
1D-Convolutional	300	2
1D-Convolutional	300	2
1D-Convolutional	6	2
1D-Convolutional	100	1
Dense	1	1
R2 score	0.97	
RMSE (kWh/m2)	0.01	

B. Surrogate model

The surrogate model was developed using the simulation-based optimization data as a training set. Afterward, the data was split into a train and test set with a ratio of 67/33, and the variables were used to train a sequential Neural Network with 1 dense layer, 4 convolutional layers, and 1 dense output layer. To optimize the layers' filters(number of nodes), a Bayesian Optimization using Gaussian processes with 100 iterations is integrated to maximize the CNN coefficient of variation (R2 score) between the test set results and the model predictions (5). Finally, this process is employed to train two CNN models that predict (2) and (3), with an early stopping callback to avoid over-fitting. The optimized CNN structure, final R2 score, and Root Mean Squared Error (RMSE) are documented in Table III and Table IV. The models obtained an R2 score of 0.96 and 0.97, and an RMSE of 0.54 and 0.01, for (2) and (3) respectively. Additionally, the surrogate models' prediction execution time takes $\approx$ 0.25 (s) for each iteration, which is 100 times faster than the simulation computation time.

$$f_4\ \ (i_0, ..., \ i_n) = R_2\,(test,\ predictions) \tag{5}$$

$$i \in \ [6\ ..\ 300]\ \ - Number\ of\ filters$$
$$n = Number\ of\ layers$$

C. Hyperparameters tuning

This section describes the selected metaheuristics and the optimization problem that fine-tunes each algorithm's hyper-parameters. Two Evolutionary (EA), and two Particle Swarm Optimization (PSO) Algorithms were selected. From the EA class of algorithms, NSGAII and Indicator-Based Evolutionary Algorithm (IBEA) [11]. From the PSO class, the Speed-constrained Multi-objective PSO (SMPSO) [16], and the OMOPSO [26] were selected. The algorithms run for 500 iterations and besides each's default hyperparameters, a polynomial mutation, and an SBX crossover were added [8]. Table **??** documents each algorithm's considered hyperparameters.

	Hyperparameters	Range	Iterations
NSGAII	Population size –Ps	[30 .. 200]	500
	SBX Crossover – S	[0, 1]	
	Polynomial Mutation – Pm	[0, 1]	
IBEA	Ps	[30 .. 200]	500
	S	[0, 1]	
	Pm	[0, 1]	
SMPSO	Swarm Size - Ss	[30 .. 200]	500
	Leader Size – Ls	[30 .. 200]	
	Max iterations – i	[30 .. 200]	
	S	[0, 1]	
	Pm	[0, 1]	
OMOPSO	Ss	[30 .. 200]	500
	Ls	[30 .. 200]	
	i	[30 .. 200]	
	S	[0, 1]	
	Pm	[0, 1]	
	Epsilon -	[0.0001, 1]	

To evaluate an optimization model's performance for MOO, most performance metrics are calculated regarding the optimum solutions found by the algorithm. These solutions are called non-dominated solutions. They represent solutions that cannot improve more in one objective, without harming the other/s [7]. In this case study, the problem's non-dominated solutions illustrate the trade-offs between the cost of construction, fairness of performance among buildings, and total energy use of the buildings. Thus, an algorithm that explores the vastest solution space, tends to perform better for this particular problem. To measure this, the hypervolume of each algorithm's non-dominated solutions is calculated as a way of describing the area/volume of the solutions obtained in a ratio of a specific boundary domain [5], [6]. In this case, our boundary domain represents the highest and lowest possible thresholds for (2), (3), and (4).

The fine-tuning of the algorithms' hyperparameters can be described as a single objective optimization problem to find the combination of parameters that yields the maximum hypervolume (6) (7) (8) (9). Thus, a Bayesian Optimization with 100 iterations is integrated to find the best combination of hyperparameters for each algorithm's settings.

$$f_{NSGAII}\ (P_s,\ S,\ P_m) = H(f_1, f_2, f_3) \tag{6}$$

$$f_{IBEA}\ (P_s,\ S,\ P_m) = H(f_1, f_2, f_3) \tag{7}$$

$$f_{SMPSO}\ (S_s,\ L_s\ i,\ S, P_m) = H(f_1, f_2, f_3) \tag{8}$$

$$f_{OMOPSO}\ (S_s,\ L_s\ i,\ S, P_m,\ \varepsilon) = H(f_1, f_2, f_3) \tag{9}$$

$$H - Hypervolume;\ Boundaries\ for\ H\ calculation:$$

$$f_1 \in\ [30,\ 60]\ -\ kWh/m^2$$

$$f_2 \in\ [0.25,\ 0.50]\ -\ kWh/m^2$$

$$f_3 \in\ [400000,\ 900000] -\ €$$

III. Results and Discussion

After performing the optimizations with the fine-tuned metaheuristics, the algorithms' non-dominated solutions are calculated and plotted according to the results of each objective. The results are illustrated in Fig. 3. It is visible that the algorithms obtained different results regarding the exploration of the objective space. SMPSO and OMOPSO explored a wider range of values, while IBEA focused more on one area of the solution space. The NSGAII explored an acceptable area but failed to find solutions for higher (2) and lower (3) and (4) such as the PSO algorithms. In total, the algorithms explored a solution space with values of (2) between ≈ 45 and ≈ 55 kWh/m2, (3) between ≈0.30 and ≈0.40 kWh/m2, and (4) between ≈ 400,000 and ≈ 600,000 €.

Table V documents the algorithms hypervolume for the optimum values of their hyperparameters. The IBEA algorithm obtained the best hypervolume of 0.54, followed by the NSGAII, with 0.53, and SMPSO and OMOPSO, with 0.52. Additionally, it is visible in Fig.3 that IBEA obtained the higher hypervolume because it focused on a specific area, not because it explored the vastest solution space. Thus, IBEA successfully found better optimum solutions but ultimately failed in the exploration of the solution space and its inherent trade-offs between the buildings' energy usage, standard deviation, and cost of construction. For these reasons, the NSGAII algorithm, which obtained the highest hypervolume and explored a balanced solution space, was chosen to perform the final optimization.

TABLE V
Optimum metaheuristics hyperparamters and respective hypervolumes

	Hyperparameters	Value	Hypervolume
NSGAII	P_s	30	0.53
	S	1	
	P_m	0.59	
IBEA	P_s	32	0.54
	S	0.66	
	P_m	1	
SMPSO	S_s	68	0.52
	L_s	59	
	i	67	
	S	0.43	
	P_m	0.35	
OMOPSO	S_s	30	0.52
	L_s	200	
	I	200	
	S	1	
	P_m	0	
	ϵ	0.001	

The NSGAII algorithm was run with the optimum hyperparameters found for 10000 iterations and the non-dominated

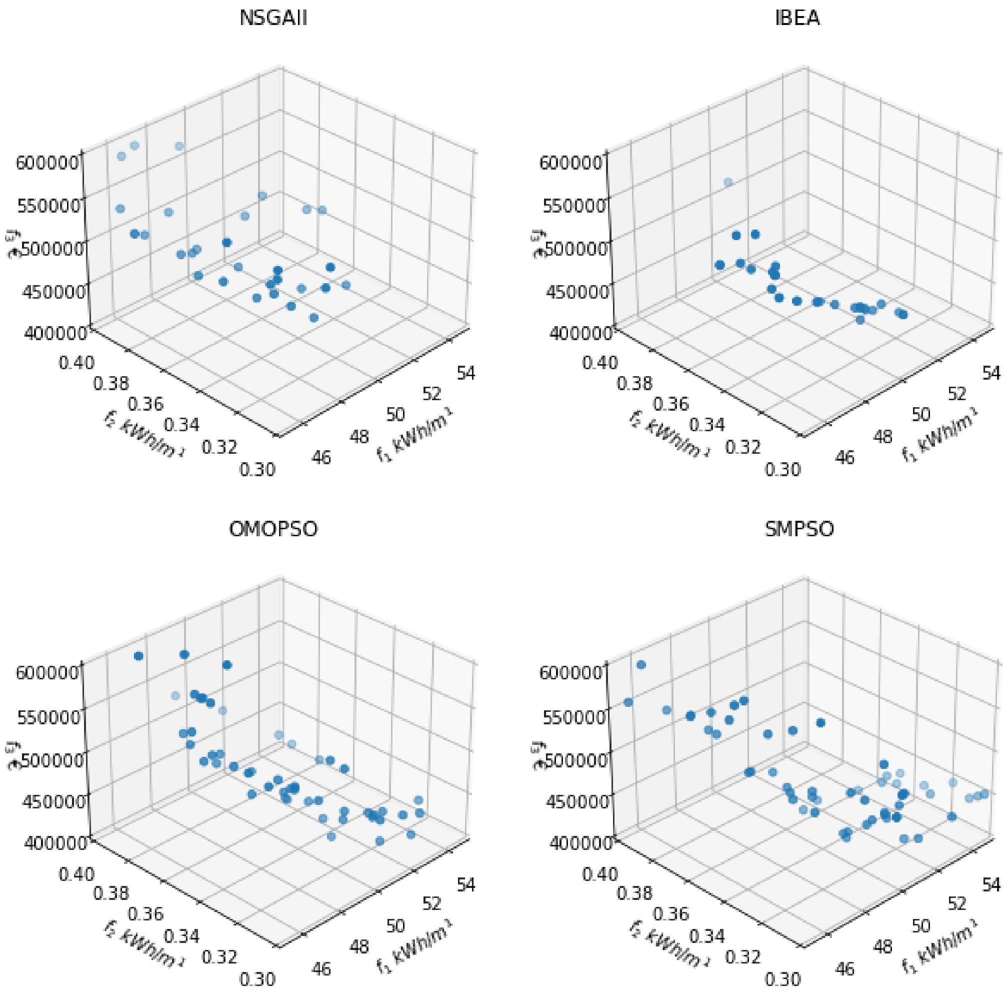

Fig. 3. Plotted non-dominated solutions of optimized metaheuristics

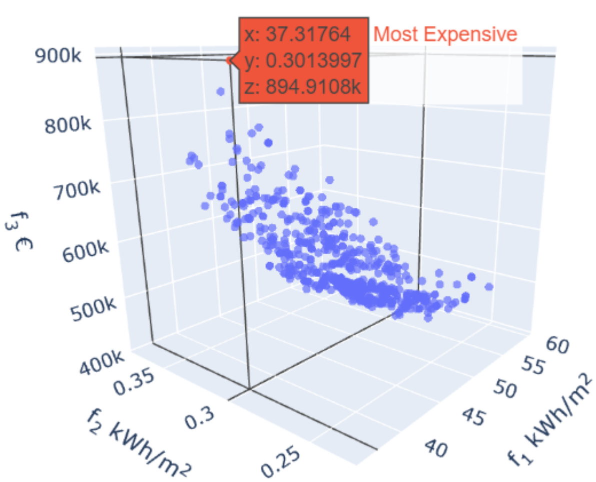

Fig. 4. NSGAII non-dominated solutions for 10000 iterations - The most expensive solution is represented in red.

solutions found were simulated to validate the surrogate model predictions. Results show a hypervolume of 0.60, which is significantly larger when compared with the values obtained for the 500 iterations in Table V. Additionally, Fig. 4 shows that the algorithm explored values between 40 and 60 kWh/m^2, 0.2 and 0.5 kWh/m^2, and 400000 and 900000 €. With these results, it is possible to discern the existing trade-offs between energy consumption, fairness of performance among buildings, and total cost of construction. Moreover, assuming this construction has a fixed budget, it is possible to find the best available solution with a minimum f_1 and f_2. Finally, Fig.4 also shows how a solution with the most expensive constructions for all surfaces is not necessarily the best solution, with the algorithm finding a significant number of cheapest solutions with lower f_1 and f_2, which can allow savings of up to 22% (200000 €) on the total cost of construction, while maintaining the same performance.

These results have shown that for this particular BPO problem, different algorithms explored different solution spaces. These can be more or less suitable for the practitioner's decision-making goals. Particularly, they show that the algorithm with the highest hypervolume did not explore the desired solution space. Additionally, with the integration of surrogate models in the optimization process for these functions, a process that could take up to weeks of computing time is reduced to days or hours, which provides a significant boost to the integration of these practices in the industry and policy fields.

IV. Conclusions

Because most building and urban optimization problems typically have objectives that are outputs of analysis and simulation tools, and because these take significant time to yield results, it is often unfeasible to perform a correct optimization process [17], [20], [22], [31]. This work integrates a surrogate model approach in the optimization structure that allows us to perform a standard pipeline of activities for the optimization of a time-consuming function in an acceptable time frame. The steps and processes required are structured into one seamless framework that can speed up simulation times up to 100 (for this particular problem), with acceptable accuracy. In spite of this methodology focusing on a particular problem, research shows that these approaches are particularly efficient and can be applicable transversely to other optimization problems within the building performance realm such as computational fluid dynamics, agent-based modeling, Daylighting, and Structural analysis, among others.

Alas, because of the computational complexity of building performance simulation and optimization, practitioners still avoid integrating such processes. Fortunately, surrogate models are efficient in not only reducing the time it takes for simulations to run but also in reducing the number of input features required to obtain results. Thus, to bridge the existing computational gap between practitioners and these processes, future work must focus on the creation of surrogate models that are easier to grasp than simulation models, the benchmark of specific algorithms for BPO problems, and the development of end-user interfaces with automated optimization, surrogate development, and hyperparameter tuning processes for benchmarked BPO problems.

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