An Efficient Evolutionary Approach to Parameter Identification in a Building Thermal Model

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Abstract—Thermal models of buildings are often used to identify energy savings within a building. Given that a significant proportion of that energy is typically used to maintain building temperature, establishing the optimal control of the buildings thermal system is important. This requires an understanding of the thermal dynamics of the building, which is often obtained from physical thermal models. However, these models require detailed building parameters to be specified and these can often be difficult to determine. In this paper, we propose an evolutionary approach to parameter identification for thermal models that are formulated as an optimization task. A state-of-the-art evolutionary algorithm, i.e., SaNSDE+, has been developed. A fitness function is defined, which quantifies the difference between the energy-consumption

time-series data that are derived from the identified parameters and that given by simulation with a set of predetermined target model parameters. In comparison with a conventional genetic algorithm, fast evolutionary programming, and two state-of-the-art evolutionary algorithms, our experimental results show that the proposed SaNSDE+ has significantly improved both the solution quality and the convergence speed, suggesting this is an effective tool for parameter identification for simulated building thermal models.

Index Terms—Building thermal model, differential evolution (DE), evolutionary optimization, parameter identification.

NOMENCLATURE

DE	Differential evolution.
SaNSDE	Self-adaptive DE with neighborhood search.
SaNSDE+	Improved SaNSDE.
JADE	Adaptive DE variant.
SGA	Standard genetic algorithm.
FEP	Fast evolutionary programming.
PSO	Particle swarm optimization.
CLPSO	Comprehensive learning PSO.
NP	Population size.
F	Scale factor of DE.
CR	Crossover rate of DE.
CR _m	Mean of Gaussian distribution for generating CR.
CR _{rec}	Recorded CR values for CR _m updating.
Δf_{rec}	Recorded fitness improvements.
p	Control parameter in the mutation of SaNSDE+.

I. INTRODUCTION

ENERGY consumption of buildings has steadily increased, reaching figures between 20% and 40% of the total energy consumed in developed countries [1]. Therefore, building energy efficiency is of prime concern and identifying energy savings beyond the obvious is becoming an increasingly important yet challenging task. Automated meter reading (AMR) systems, or smart meters, are often suggested as a solution. However, once the consumption data are captured, how to make use of these data to improve building energy efficiency is still an open issue.

One approach is to use the collected energy data to build a data-driven thermal model of the building, which can be used to estimate the thermal-energy demands of that building [2]. Comparison of the estimated demand with the metered consumption data can be a useful monitoring tool. Previous approaches to

Manuscript received May 20, 2011; revised October 2, 2011; accepted October 16, 2011. Date of publication December 15, 2011; date of current version October 12, 2012. This work was supported in part by the National Natural Science Foundation of China under Grant U0835002, Grant 61028009, and Grant 61175065, by the National Natural Science Foundation of Anhui Province under Grant 1108085J16, by the Engineering and Physical Sciences Research Council under Grant EP/F062567/1 on “Advanced Analysis of Building Energy Performance using Computational Intelligence Approaches,” and by the European Union 7th Framework Program under Grant 247619. This paper was recommended by Associate Editor N. O. Attoh-Okine.

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Digital Object Identifier 10.1109/TSMCC.2011.2174983

deriving thermal models of buildings have been proposed for electrical load estimation, such as [3]–[7]. These data-driven methods are not computationally efficient and do not easily lend themselves to building energy management and control systems since the results are often difficult to interpret.

In order to capture, within a simulation, i.e., the thermal dynamics apparent within a building, a reasonable account of the physical thermal behavior is required. Examples of simulation software that are intended for this purpose include ESP-r [8], TRNSYS [9], DOE-2 [10], BLAST, Energy Plus [11], TAS [12], FLUENT [13], and DEROB-LTH [14]. In this study, we use HAMBBase [15], which is capable of simulating the indoor temperature, the indoor air humidity, and energy used for heating and cooling of a multizone building [16]. The program runs within the MATLAB environment.

A drawback of relying on these types of physical models is that they require a significant number of parameters, describing the characteristics of the building, to be defined in advance. Unfortunately, for most real buildings, many of these parameters are unknown and difficult to obtain, such as the characteristics of the construction materials.

In this study, we consider the identification of these thermal model parameters to be an optimization task, where the objective is to minimize the disparity between the estimated energy consumption of the model and the actual metered energy consumption of the building. This requires only energy consumption data to be collected from the buildings' AMR system.

Such a parameter-identification problem could be tackled with traditional optimization algorithms. However, most are gradient based and have the following drawbacks [17]:

- 1) they are often sensitive to the starting state;
- 2) they have a high probability of getting trapped at local optima for multimodal optimization problems;
- 3) they often require continuity and differentiability of the objective function.

The HAMBBase model results in a nontrivial mapping from model parameters to the model energy consumption because of the dynamic nature of thermal models. This makes it very difficult to achieve the required continuity and differentiable characteristics. Therefore, a black-box optimization method is required, which avoids these drawbacks, such as an evolutionary optimization approach [18].

Evolutionary optimization methods utilize a population-based stochastic search process and require little prior knowledge. Successful attempts have been suggested for many real-world applications [19], [20]. Specifically, in the study of heating, ventilating, and air conditioning (HVAC) system designs, genetic algorithms (GAs) have been applied to the optimization of HVAC system sizing [21], the simultaneous optimization of building construction, system supervisory control [22], and, most recently, the optimization of HVAC system configurations [23]. Related work has also been reported in the area of building model parameter identification [24]–[26]. However, rather than using an extensive physical model and considering it to be a black-box system, they mainly focused on the development of simplified building models. The

Fig. 1. Simple flowchart to demonstrate how the HAMBBase model works.

evolutionary optimization methods that are used tend to be “off the shelf” generic algorithms.

In recent years, developments in evolutionary computation (EC) have led to many effective and efficient variants of evolutionary algorithms (EAs), which have been applied to numerous real-world applications. In the light of this, it seems that the application of evolutionary optimization deserves more investigation for the problem of parameter identification in thermal models of buildings.

In this paper, we discuss the application of a state-of-the-art EA, i.e., the SaNSDE [27], to parameter identification for a building thermal model. The efficacy of the SaNSDE algorithm has already been verified on a broad number of benchmark functions in [27] and [28]. Modifications to the original SaNSDE algorithm were made, by the introduction of a more efficient mutation strategy, to further improve its convergence speed for the parameter identification task that is described in this study. This improved SaNSDE variant is denoted as SaNSDE+.

For experimental validation, parameter identification problems were formulated using simulated building thermal models. The performance of the SaNSDE+ algorithm, on this building thermal-model parameter identification task, is compared with ten variants of two well-known EAs, i.e., the SGA [29] and FEP [30], and two state-of-the-art EA variants, i.e., CLPSO [31] and JADE [32].

The rest of this paper is organized as follows. In Section II, we provide a brief overview about the adopted building thermal model. In Section III, we present the formulation and the fitness function for the parameter identification problem in building thermal models. In Section IV, we introduce the utilized optimization algorithms, i.e., SaNSDE and the new improved version SaNSDE+. In Section V, we present the experimental studies. Finally, in Section VI, we conclude this paper with some remarks and topics for future work.

II. OVERVIEW OF THE BUILDING THERMAL MODEL

The utilized HAMBBase¹ is a physical model for the simulation of heat and vapor flows in a building. With the model, the indoor temperature, the indoor air humidity, and the energy use for heating and cooling of a multizone building can be simulated. A simple flowchart of the simulation process is demonstrated in Fig. 1.

¹For a more detailed explanation of the HAMBBase model see [33].

In HAMBase, the smallest entity of the building is a zone, which can be one room but also a number of adjacent rooms with more or less equal climatic conditions. The model of a zone consists of a thermal model and a hygric model, and the main result of HAMBase is the thermal and hygric indoor climate and the energy use to maintain this climate. In order to develop such a model with desired simulation accuracy, the following issues were considered in HAMBase [15]:

- 1) heat and mass balance;
- 2) indoor climate model, which is further divided into the thermal indoor climate and the hygric indoor climate;
- 3) the envelope model, which is further divided into the thermal model and the hygric model;
- 4) fenestration, which includes the incident solar radiation, the heat flow through fenestration, the solar radiation absorbed in a zone, the daylight factor, and the airflow window;
- 5) air infiltration, which includes the simulation of airflows by natural ventilation that is caused by wind pressures and stack effects;
- 6) heating/cooling system, which includes the floor, walls, and ceiling heating or cooling systems;
- 7) mass sources, for which both the evaporation of liquid water and the inert gas are considered.

These issues, which are crucial in the construction of the whole HAMBase model, are basically implemented according to related physical principles. More detailed information about them can be found in [15].

To illustrate the complexity of the HAMBase model, we further describe how the heat and mass balance is handled. The thermal behavior of a zone in HAMBase depends on the following heat and moisture balance equations:

$$\text{heat loss} + \text{heat stored} = \text{heat gains} + \text{auxiliary heat}$$

$$\text{moisture loss} + \text{moisture stored}$$

$$= \text{vapor production} + \text{humidification}$$

where:

- 1) *heat loss* is the transmitted and infiltrated energy losses through the envelope of a building;
- 2) *heat stored* is the energy stored by the building construction, which is related to the materials and size of the building;
- 3) *heat gains* are derived from the solar radiation, artificial lighting, domestic hot water, appliances, and so on;
- 4) *auxiliary heat* is supplied or extracted by a heating or cooling plant, respectively.

The moisture in the building is related to the diffusion and advection through the envelope, where:

- 1) *moisture loss* is the vapor losses by airflows;
- 2) *moisture stored* is the water held in porous materials;
- 3) *vapor* is produced by people, plants, appliances, etc;
- 4) *humidification* is needed for obtaining a relative humidity in the zone.

While these underlying equation are relatively simple, they interact with the state of the simulated building and external environment. This can generate significantly complex dynamic

Fig. 2. Outline of the HAMBase for the building model.

behavior in terms of the times-series outputs that are produced from the simulation. An overview of the relevant inputs and outputs of the model is outlined in Fig. 2.

While some of the parameters are relatively easy to determine by direct measurement, such as heating/cooling plant behavior, zone topology, and volume, some are much more difficult to obtain, such as the building materials and occupant behavior. Given all required model parameters, the indoor temperature, the indoor air humidity, and energy consumption for heating and cooling of a multizone building can be obtained through simulation.

A reference model, which is included with the HAMBase software, is used, which provides sufficient complexity in operation while simplifying the process of development of a suitable model. Predetermined features of the reference model include the following:

- 1) simulation and operation periods for the building, occupants, and building systems;
- 2) construction and layout of the building into four zones;
- 3) performance and behavior of the HVAC components;
- 4) the properties of a finite set of materials that are used within the building include: material thickness [m],

TABLE I
OBJECTIVE PARAMETERS OF THE BUILDING MODEL

ID	Given	Description
x_1	0.13	External wall: internal surface heat transfer resistance [Km^2/W]
x_2	0.04	External wall: surface heat transfer resistance at the opposite site [Km^2/W]
x_3	0.90	External wall: external solar radiation absorption coefficient
x_4	0.90	External wall: external long-wave emissivity
x_5	0.13	Internal wall: internal surface heat transfer resistance [Km^2/W]
x_6	0.13	Internal wall: surface heat transfer resistance at the opposite site [Km^2/W]
x_7	0.13	Roof construction: internal surface heat transfer resistance [Km^2/W]
x_8	0.04	Roof construction: surface heat transfer resistance at the opposite site [Km^2/W]
x_9	0.80	Roof construction: external solar radiation absorption coefficient
x_{10}	0.90	Roof construction: external long-wave emissivity

The actual values used in the simulation are listed in the *Given* column.

internal surface heat transfer resistance [$K \cdot m^2/W$], surface heat transfer resistance at the opposite site [$K \cdot m^2/W$], external solar radiation absorption coefficient, and external long-wave emissivity;

- 5) the meter sampling intervals for all measured time-series output variables of the simulation, which include temperature, relative humidity, and energy consumption. In this case, the sampling rate is set to 1 h.

The key parameters of the HAMBBase model we are concerned with, in this case, are listed in Table I. These represent the apparent material properties of the simulated building. These variables are chosen for parameter identification because of the difficulty in quantifying them in practice.

The reason we choose HAMBBase as the simulation model is because it has several remarkable advantages. First, the designers based it on physics, which makes the model very realistic, instead of tuning it with results from a sophisticated transient model. Second, the simulation environment is transparent, and thus, the implementation of models is relatively easy [16]. Third, rather than commercial software, it facilitates open-source modeling, and all the simulation environment are publicly available from the website [33]. Although HAMBBase might have its own limitations, such as numerous control parameters, too long simulation duration time, etc., it still is a practical platform to investigate the efficacy EAs for model parameter identification. Moreover, the optimization approach that is developed in this paper is taking the building model as a black box. It should not be model dependent and is expected to work for other models as well.

III. PROBLEM FORMULATION

In order to formulate a parameter identification problem as an optimization task, an objective function must be defined. In this case, the objective is to minimize the disparity between the simulated energy consumption of the thermal model and the metered consumption of the real building by adjusting model parameters. In Fig. 3, an overview of the optimization process is shown.

Fig. 3. Evolutionary optimization for the building thermal model parameter identification.

An initial population is formed from a set of randomly generated candidate parameters. Offspring are, then, generated by the application of perturbations to the candidate parameters of individuals in the current population. These offspring are evaluated based on a given fitness metric. After that, a selection strategy is used to identify a subset of the population to propagate to the next population for iteration until the stopping criterion is met.

This approach requires a clear and robust fitness evaluation (FE) method to be defined. For a given candidate solution, the basic idea of FE is to measure the deviation between the output of the real building, in the form of historical consumption and temperature data, and that of the simulated building model.

The behavior of a building could be considered to be a mapping from the time-dependent input $\mathbf{t}_i$ to the corresponding time-dependent output $\mathbf{y}(\mathbf{t}_i)$, where $i \in [1, T]$ is the index of time span. The input $\mathbf{t}_i$ could be the recorded climate data, such as the outdoor temperature, humidity, solar radiation, etc. The output $\mathbf{y}(\mathbf{t}_i)$ could be the energy consumption of the building, the internal temperature, humidity, etc., of each room in the building.

Similarly, a building model, which is designed to simulate the behavior of the real building, is also a mapping from the same input to output. The difference is that the building model is given in a parametrized form and its output depends on not only the input, but also a set of n parameters, i.e., $\mathbf{x} = (x_1, x_2, \dots, x_n) \in \mathbb{R}^n$. Therefore, the building model output could be represented by $\hat{\mathbf{y}}(\mathbf{x}, \mathbf{t}_i)$ at each time instant $\mathbf{t}_i, i \in [1, T]$. Given a set of identified parameters, the deviation between the output of the real building and that of the building model with the same input can be measured by the following function:

$$f(\mathbf{x}) = \frac{1}{T} \sum_{i=1}^T |\mathbf{y}(\mathbf{t}_i) - \hat{\mathbf{y}}(\mathbf{x}, \mathbf{t}_i)|^p \quad (1)$$

where p is a positive number. In practice, $p = 1$ and $p = 2$, which are called mean absolute error (MAE) and mean-squared error (MSE), respectively, are the most often used settings. Both

Fig. 4. Fitness landscape of the formulated problem against one of the model parameters.

MAE and MSE are suitable to serve as fitness functions, because they can reflect the goodness of a trial parameter solution. In this paper, we simply use the MAE, i.e., $p = 1$, as the fitness function. It is possible that the fitness function $f(\cdot)$ is not noise free because of the observation noise in $\mathbf{y}(\mathbf{t}_i)$. Since much of the noise can be handled via general techniques, like standard filtering or statistical analysis [34], which is quite independent of the design of optimization algorithms, we will not consider noise in this study. Based on the reputation that EAs are effective in finding robust solutions in noisy environments [35], the proposed approach, in this paper, could be applicable to noise problems by the incorporation of a certain noise-handling technique.

Although the fitness function can be represented in such a simple form as shown in (1), it does not mean that the parameter identification problem is simple as well. To illustrate the characteristics of the fitness landscape, in Fig. 4, performance against one of the parameters (i.e., x_1) is shown, in the proximity of the optimal value (i.e., 0.13), with the other parameters randomly generated in the search space. Plots of performance against other parameters, and at different points in the search space, are similar: the fitness landscape is highly multimodal, and at the same time, there is highly interdependence between parameters.

One of the main factors that determines the difficulty of an optimization problem is the complexity of the mapping from the objective vector to the fitness value. In the parameter identification problem, the fitness mapping is determined by the objective parameter vector $\mathbf{x}$, and how the building thermal model transfers the model input $\mathbf{t}_i$ (climate data, such as outdoor temperature, humidity, solar radiation, etc.) to model output $\hat{\mathbf{y}}(\mathbf{x}, \mathbf{t}_i)$ (energy consumption, indoor temperature, humidity, etc.). This means that the FE requires running simulation with other software (i.e., HAMBase). As discussed in Section I, the adopted HAMBase is a complex physical thermal model, and the mapping from model input to output is a thermodynamical simulation process. Since there is no explicit expression of the form of

such a physical model simulation, it would be difficult, if not impossible, to utilize traditional optimization methods, for which the required gradient information is obviously not available.

With $f(\cdot)$ as the fitness function, the parameter identification problem is transferred into a bound-constrained multidimensional optimization problem as follows:

$$\arg \min f(\mathbf{x}), \text{ s.t. } \mathbf{x} \in S$$

$$\mathbf{x} = (x_1, x_2, \dots, x_n)$$

$$S = \{\mathbf{x} : l_i \leq x_i \leq u_i, x_i \in \mathbb{R} \quad \forall i \in [1, n]\} \quad (2)$$

where l_i and u_i denote the predefined upper bounds and the lower bounds of the n parameters, respectively.

If we further consider the practical operational accuracy of these model parameters, a tolerance e (e.g., $e = 10^{-3}$) could be introduced to control the parameter solution accuracy. The tolerance is useful to increase search efficiency by the reduction of the overall size of the search space. With a predefined tolerance e , the original optimization problem can be transferred into an integer programming problem easily as follows:

$$\arg \min f(\mathbf{z}), \text{ s.t. } \mathbf{z} = e \cdot \mathbf{x}, \quad \mathbf{z} \in S'$$

$$\mathbf{z} = (z_1, z_2, \dots, z_n)$$

$$S' = \{\mathbf{z} : \lfloor l_i/e \rfloor \leq z_i \leq \lceil u_i/e \rceil, z_i \in \mathbb{Z} \quad \forall i \in [1, n]\}. \quad (3)$$

IV. IMPROVED DIFFERENTIAL EVOLUTION METHOD

A. Classical Differential Evolution

DE [36], [37] is a simple yet effective algorithm for numerical global optimization. It has shown excellent performance on a wide range of benchmark problems [38], [39] as well as many real-world applications [40], [41]. DE is distinguished by its novel mutation scheme. DE executes its mutation by adding a weighted difference vector between two individuals to a third individual. Then, the mutated individuals will be subject to discrete crossover and greedy selection with corresponding individuals of the last generation to produce offspring.

Individuals in DE are represented by D -dimensional vectors $\mathbf{x}_i, \forall i \in \{1, \dots, \text{NP}\}$, where D is the number of objective parameters, and NP is the population size. According to [37], the classical DE can be summarized as follows.

1) Mutation:

$$\mathbf{v}_i = \mathbf{x}_{r_1} + F \cdot (\mathbf{x}_{r_2} - \mathbf{x}_{r_3})$$

where $r_1, r_2, r_3 \in [1, \text{NP}]$ are random and mutually different integers, and they are also different with the vector index i . The scale factor $F > 0$ is a real constant factor and is often set to 0.5.

2) Crossover:

$$\mathbf{u}_i(j) = \begin{cases} \mathbf{v}_i(j), & \text{if } U_j(0, 1) \leq \text{CR or } j = j_{\text{rand}} \\ \mathbf{x}_i(j), & \text{otherwise} \end{cases}$$

where $U_j(0, 1)$ stands for the uniform random number between 0 and 1, and j_{rand} is a randomly chosen index to ensure that the trial vector $\mathbf{u}_i$ does not duplicate $\mathbf{x}_i$. $\text{CR} \in (0, 1)$ is the crossover rate and often set to 0.9.

3) Selection:

$$\mathbf{x}'_i = \begin{cases} \mathbf{u}_i, & \text{if } f(\mathbf{u}_i) \leq f(\mathbf{x}_i) \\ \mathbf{x}_i, & \text{otherwise} \end{cases}$$

where $\mathbf{x}'_i$ is the offspring of $\mathbf{x}_i$ for the next generation. (Without loss of generality, we consider only the minimization problem in this paper).

There exist a number of DE variants based on different mutation strategies:

$$\mathbf{v}_i = \mathbf{x}_{r_1} + F \cdot (\mathbf{x}_{r_2} - \mathbf{x}_{r_3}) \quad (4)$$

$$\mathbf{v}_i = \mathbf{x}_{\text{best}} + F \cdot (\mathbf{x}_{r_1} - \mathbf{x}_{r_2}) \quad (5)$$

$$\mathbf{v}_i = \mathbf{x}_i + F \cdot (\mathbf{x}_{\text{best}} - \mathbf{x}_i) + F \cdot (\mathbf{x}_{r_1} - \mathbf{x}_{r_2}) \quad (6)$$

$$\mathbf{v}_i = \mathbf{x}_{\text{best}} + F \cdot (\mathbf{x}_{r_1} - \mathbf{x}_{r_2}) + F \cdot (\mathbf{x}_{r_3} - \mathbf{x}_{r_4}) \quad (7)$$

$$\mathbf{v}_i = \mathbf{x}_{r_1} + F \cdot (\mathbf{x}_{r_2} - \mathbf{x}_{r_3}) + F \cdot (\mathbf{x}_{r_4} - \mathbf{x}_{r_5}) \quad (8)$$

where $\mathbf{x}_{\text{best}}$ is the best individual in the current population.

Schemes (4) and (6), with notations as “DE/rand/1” and “DE/current-to-best/2”, are the most often used in practice because of their good performance [37], [42].

Most recently, we proposed a new mutation strategy “DE/current-to-local- p -best/2” in [43] as follows:

$$\mathbf{v}_i = \mathbf{x}_i + F \cdot (\mathbf{x}_{\text{lpbest}} - \mathbf{x}_i) + F \cdot (\mathbf{x}_{r_1} - \mathbf{x}_{r_2}) \quad (9)$$

where $p \in (0, 1]$, and $\mathbf{x}_{\text{lpbest}}$ is randomly chosen from a set $\mathcal{A}$ that is generated as follows at the beginning of each generation.

- 1) Set $\mathcal{A} = \emptyset$.
- 2) Randomly assign each individual to K groups, where $K = \lfloor p * \text{NP} \rfloor$, and NP is the population size.
- 3) Add the best individual in each group to $\mathcal{A}$.

The new “DE/current-to-local- p -best/2” is actually a generalization of the previous schemes, i.e., “DE/current-to-best/2” and “DE/current-to- p -best/2” [32]. Instead of using only the best individual, i.e., $\mathbf{x}_{\text{best}}$, the new mutation strategy adopts a set of superior individuals, i.e., $\mathbf{x}_{\text{lpbest}}$, to produce differential vectors. This will obviously increase the diversity of mutated individuals, and weaken the overwhelming influence of the current best individual $\mathbf{x}_{\text{best}}$. Based on the investigation in [43], DE with this mutation scheme is able to utilize the information of good solutions without the introduction of the high probability of being trapped by local optima, which is the main drawback of the other schemes that simply use $\mathbf{x}_{\text{best}}$.

B. Improved Self-Adaptive Differential Evolution With Neighborhood Search

As presented in Section IV-A, the conventional DE has several candidate mutation schemes, and three control parameters, i.e., population size NP, scale factor F , and crossover rate CR. Its performance is often highly dependent on the used mutation scheme and parameter settings. Apart from the parameter NP (which is common for all population-based algorithms), mutation strategy selection, parameters F , and CR adaptations are the three most important issues of DE research. Much work has been done along these lines. The relationship between the control parameters and population diversity has been analyzed in [44].

Experimental parameter studies and empirical parameter settings of DE have been carried out in [45] and [46]. Self-adaptive strategies have also been investigated to adapt these control parameters [47], as well as different mutation schemes [42].

In [27], we proposed a new DE variant, namely SaNSDE, to adapt the two control parameters, i.e., F and CR, and the choice of mutation schemes. Three self-adaptive mechanisms are utilized in SaNSDE, which are summarized as follows.

- 1) Self-adaptive selection of mutation scheme based on two candidates, where SaNSDE utilizes mutation schemes (4) and (6) as candidates and produces the trial vector based on

$$\mathbf{v}_i = \begin{cases} \text{Equation (4)}, & \text{if } U_i(0, 1) < p \\ \text{Equation (6)}, & \text{otherwise.} \end{cases} \quad (10)$$

Initially, the parameter p is set to 0.5. After evaluation of all offspring, the number of offspring successfully entering the next generation, while generated by (4) and (6), are recorded as ns_1 and ns_2 , respectively, and the numbers of offspring discarded, while generated by (4) and (6), are recorded as nf_1 and nf_2 . Those two pairs of numbers are accumulated within a specified number of generations (50 in SaNSDE), called the “learning period.” Then, the probability p is updated according to

$$p = \frac{ns_1 \cdot (ns_2 + nf_2)}{ns_2 \cdot (ns_1 + nf_1) + ns_1 \cdot (ns_2 + nf_2)}. \quad (11)$$

Here, ns_1 , ns_2 , nf_1 , and nf_2 will be reset once p is updated after each learning period.

- 2) Self-adaptation of scale factor F using either the Gaussian or the Cauchy distribution. SaNSDE generates F_i for each individual based on

$$F_i = \begin{cases} N_i(0.5, 0.3), & \text{if } U_i(0, 1) < fp \\ C_i(0, 1), & \text{otherwise} \end{cases} \quad (12)$$

where fp is self-adapted as p is done according to (11), except that here we have to record the corresponding F values, which make offspring enter the next generation successfully. $N_i(0.5, 0.3)$ denotes a Gaussian random number with mean 0.5 and standard deviation 0.3. $C_i(0, 1)$ denotes a Cauchy random number with the location parameter 0 and scale parameter 1.

- 3) Self-adaptive crossover rate CR with the Gaussian distribution. SaNSDE allocates CR_i for each individual according to

$$\text{CR}_i = N_i(\text{CRm}, 0.1). \quad (13)$$

Here, CRm is, initially, set to 0.5. These CR values for all individuals remain the same for several generations (5 in SaNSDE), and then, a new set of CR values is generated using the same equation. During every generation, the CR values that are associated with offspring successfully entering the next generation are recorded in an array CR_{rec} , and the corresponding improvement on fitness values are also recorded in another array Δf_{rec} . After a specified number of generations (25 in SaNSDE), CRm will be

updated:

$$\text{CRm} = \sum_{k=1}^{|\text{CR}_{\text{rec}}|} w_k * \text{CR}_{\text{rec}}(k)$$

$$w_k = \Delta f_{\text{rec}}(k) / \left(\sum_{k=1}^{|\Delta f_{\text{rec}}|} \Delta f_{\text{rec}}(k) \right)$$

where CR_{rec} and Δf_{rec} will be reset once CRm is updated.

Since the FE of a simulated building energy model can be computationally expensive, the convergence speed of EAs for parameter identification is very important. To further increase the convergence speed of SaNSDE, we revise its self-adaptation mechanisms as follows.

- 1) The candidate mutation scheme (6) is replaced with the most recent one (9), i.e.,

$$\mathbf{v}_i = \begin{cases} \text{Equation(4)}, & \text{if } U_i(0, 1) < p \\ \text{Equation(9)}, & \text{otherwise.} \end{cases} \quad (14)$$

- 2) The Cauchy random number $C_i(0, 1)$ in (12) is replaced with $C_i(0.5, 0.3)$, because it was found that F values around 0.5 are more likely to produce successful mutation [45].

This new improved variant is denoted as SaNSDE+. Both SaNSDE and SaNSDE+ will be applied to the parameter identification problems that are formulated in Section III. To make them able to operate in integer search space, slight modification is performed by rounding off the real parameter values to the nearest integers [48]. The integer version of these two algorithms are denoted as [SaNSDE] and [SaNSDE+].

V. EXPERIMENTAL STUDIES

A. Setup

In this study, we investigate the application of evolutionary methods (e.g., SaNSDE and SaNSDE+) for parameter identification of a building thermal model. In order to determine the performance of this approach for a real building, we would need to know the correct value of the relevant building parameters, to ensure that the parameters that are identified using the thermal model correspond correctly. For a real world building, this would require the collection of both historical consumption data and the corresponding values for the model parameters. This is a costly and time-consuming process, which is beyond the scope of this study.

Therefore, a simulation instance of the adopted building model is used as the target. The instance building can be achieved easily by providing a set of valid parameter values for the building model.

The target instance building has four zones, which is the typical setting of a basic building simulation. The inputs of the building simulation are the outside temperatures and humidities for a period of time (e.g., 1 mo). The outputs of the building simulation includes the temperatures and humidities of all the zones, and the total energy consumption of the building corresponding to the input time period. The I/O data were taken from

Fig. 5. I/O data of the target instance building, including the outdoor and indoor (only the first room is shown) temperature and humidity, and energy consumption of the building.

a time period of 1 mo² real climate data of De Bilt starting from the Oct. 1, 1998, which can be seen from Fig. 5. The data were collected at discrete hourly time steps. This resulted in a total of $31 * 24 = 744$ data points.

The objective parameters of the building model and their physical significance can be found in Table I. Based on the given objective parameters, two problems with different complexities can be formulated as follows.

- 1) The six-parameter problem: optimizing only the first six parameters in Table I, with the remaining parameters being predefined as their optimal values.
- 2) The ten-parameter problem: optimizing all the ten listed parameters.

As for the parameter settings of the four adopted DE variants (i.e., SaNSDE, SaNSDE+, [SaNSDE], and [SaNSDE+]), population size $\text{NP} = 50$ was used for all of them. The probability for choosing local “pbest” was set to $p = 0.1$ in [SaNSDE+] and SaNSDE+ [43]. The number of generations was set to 1000 for the six-parameter problem, and 2000 for the ten-parameter problem. The search ranges for all objective parameters were set to $\{x_i \in [0, 1] \ \forall i \in [1, 10]\}$.

The initial population was generated randomly in the search space. The tolerance for integer programming was set to $e = 10^{-3}$, which means the corresponding search space was transferred to

$$\{x_i = z_i * e, z_i \in [0, 1000] \ \forall i \in [1, 10]\}$$

for [SaNSDE] and [SaNSDE+].

B. Results

The simulation results over 30 independent runs of the four tested DE variants on the six-parameter and ten-parameter problems are summarized in Tables III and IV, respectively. In these tables, smaller values indicate better performance than larger

²Validation with large dataset (9 mo) was provided in Section V-D.

TABLE II
BEST PARAMETER SOLUTION FOUND BY EACH ALGORITHM

ID/Given	[SaNSDE]	[SaNSDE+]	SaNSDE	SaNSDE+
x_1 / 0.13	0.13	0.13	0.13	0.13
x_2 / 0.04	0.04	0.04	0.04	0.04
x_3 / 0.90	0.90	0.90	0.90	0.90
x_4 / 0.90	0.90	0.90	0.90	0.90
x_5 / 0.13	0.13	0.13	0.13	0.13
x_6 / 0.13	0.13	0.13	0.13	0.13
x_7 / 0.13	0.13	0.13	0.13	0.13
x_8 / 0.04	0.04	0.04	0.0399999	0.0399999
x_9 / 0.80	0.80	0.80	0.800001	0.800001
x_{10} / 0.90	0.90	0.90	0.900001	0.900001

Optimal parameter values are given in the *Given* column.

TABLE III
SIMULATED RESULTS ON THE SIX-PARAMETER PROBLEM OVER 30 RUNS

	[SaNSDE]	[SaNSDE+]	SaNSDE	SaNSDE+
Best	0.00e+00	0.00e+00	2.07e-08	1.45e-08
Median	1.62e-03	0.00e+00	3.39e-08	1.96e-08
Worst	4.82e-02	1.41e-02	6.54e-08	2.42e-08
Mean	6.81e-03	5.59e-04	3.55e-08	1.99e-08
Std	1.09e-02	2.60e-03	8.71e-09	2.64e-09
SR	14/30	28/30	30/30	30/30

“SR” means the successful runs over the 30 runs.

TABLE IV
SIMULATED RESULTS ON THE TEN-PARAMETER PROBLEM OVER 30 RUNS

	[SaNSDE]	[SaNSDE+]	SaNSDE	SaNSDE+
Best	0.00e+00	0.00e+00	7.16e-08	5.40e-08
Median	3.17e-02	4.52e-03	8.95e-08	7.86e-08
Worst	8.09e-02	6.36e-02	4.98e-02	1.71e-07
Mean	3.51e-02	1.60e-03	2.82e-03	8.96e-08
Std	2.51e-02	2.02e-02	1.01e-02	3.17e-08
SR	5/30	12/30	27/30	30/30

“SR” means the successful runs over 30 runs.

values, because the fitness function was given based on the error of the building thermal model. Statistical indicators, such as “Best,” “Median,” “Mean,” “Worst,” and “Std” (standard deviation) values over 30 independent runs, are provided to ensure a fair comparison of performance between the tested algorithms.

A run is regarded as successful if the final fitness value is 0 for integer programming, or smaller than 10^{-5} for real-coded EA. The ratio of successful runs is denoted by “SR.”

For each algorithm the best fitness achieved is very small or 0 but we can validate these model parameters themselves by comparing them to the instance parameters used in the original simulation.

This is shown in Table II, in which the best parameter solutions found by each of the algorithms on the ten-parameter problem are listed. The real-coded SaNSDE and SaNSDE+ found slightly different parameter values for x_8 , x_9 , and x_{10} . [SaNSDE] and [SaNSDE+] provided the more accurate results because the search accuracy of them were limited at the level of $e = 10^{-3}$.

For the results of six-parameter problem in Table III, [SaNSDE] were trapped in local optimum frequently (SR = 14/30), while [SaNSDE+] found the optimal solution with much better probability (SR = 28/30). There is not much difference between SaNSDE and SaNSDE+ on this problem. However, for the more complex ten-parameter problem in Table IV, the difference between them are more significant. [SaNSDE] (SR = 5/30) is more likely to be trapped in local optima

than [SaNSDE+] (SR = 12/30). For the real-coded algorithms, SaNSDE+ can still find the near-optimum consistently, but the successful rate of SaNSDE dropped to SR = 27/30.

The evolution curves of these algorithms are also provided in Fig. 6. The convergence speed of SaNSDE+ and [SaNSDE+] appears to be generally faster than SaNSDE and [SaNSDE], respectively. This confirms that the proposed improvements in SaNSDE+ work well. Another interesting point is that real-coded algorithms often converged faster than the integer programming algorithms. This might be because DE is originally designed for real-coded optimization, and the method of discretizing the parameter values into an integer domain influences their efficiency.

Based on the achieved results, SaNSDE+ is the most recommended one among all the tested evolutionary optimization methods. It can be concluded that the proposed SaNSDE+ is sufficiently capable of the parameter identification problems in building thermal models.

C. Comparison With Classical EAs

To further verify the efficacy of our method, we also compared the performance of SaNSDE+ with two other well-known EAs, i.e., SGA [29] and FEP [30]. Many former studies have demonstrated that they are the appropriate algorithms for evolutionary parameter identification. In the literature [25], [26], GA was used to estimate the parameters of some simplified building models using the operation data collected from site monitoring. Various case studies were conducted to validate the efficacy of the parameter optimization method. As for FEP, in [49], it was successfully used to determine unified creep damage constitutive equations, which were formulated as a complex, nonconvex, and nondifferentiable global optimization problem. In [50], in order to obtain a reasonably good description of the luminosity profiles of galaxies, FEP was used to fit the parameters for functional forms identified in the previous step. The proposed approach has been applied to modeling 18 elliptical galaxies profiles.

Since both the two algorithms have some control parameters, which may affect their performance greatly, we tested several variants of them with different parameter settings. For the SGA, the control parameters are the chromosome length L for each variable, crossover rate CR, mutation probability “pm,” and two candidate selection schemes, i.e., stochastic universal sampling (SUS) and roulette wheel selection (RWS). According to [51], we set CR = 0.7, and pm = 0.7/ L . Other parameters were tuned to formulate the following four different SGA variants.

- 1) *SGA-10S*: Using length $L = 10$, and the SUS selection scheme. $L = 10$ implies the accurate level of objective parameters is 10^{-3} , which is consistent with our setting for the integer programming problem.
- 2) *SGA-10R*: Using length $L = 10$, and the RWS selection scheme.
- 3) *SGA-20S*: Using length $L = 20$, and the SUS selection scheme. Setting L to 20 is likely to generate more accurate

Fig. 6. Evolution curves for the six-parameter (left) and ten-parameter (right) problems. All results have been averaged over 30 independent runs.

results and makes the algorithm act like real-coded ones (e.g., SaNSDE+).

- 4) *SGA-20R*: Using length $L = 20$, and the RWS selection scheme.

For FEP, the control parameters are the tournament selection size q , and the initial strategy parameter η . It was also claimed that a small lower bound for controlling strategy parameters [52] and swapping the order of varying objective variables and strategy parameters may improve FEP's performance [30]. As suggested in the original FEP algorithm, we set $\eta = 3.0$ and tuned other parameters, which resulted in the following six FEP variants.

- 1) *FEP-2N*, *FEP-5N*, and *FEP-10N*: The original FEP with $q = 2, 5, 10$ as the tournament size, respectively. No other strategy was used to further improve FEP.
- 2) *FEP-2Y*, *FEP-5Y*, and *FEP-10Y*: FEP with $q = 2, 5, 10$ as the tournament size, respectively. Swapping the order of varying objective variables and strategy parameters, and using 10^{-4} as the lower bound for strategy parameters.

For SaNSDE+, since most of its parameters are self-adapted, we only need to set $p = 0.1$, which is the probability for choosing local "pbest."

For all the tested algorithms, $NP = 50$ was used as the population size. To provide a fair comparison, the same number of FEs was used for them. The code of SGA was taken from the publicly available toolbox GATBX [51], while the other algorithm FEP was implemented based on the description in [30].

The results of all the algorithms on the ten-parameter problem are summarized in Table V. It is obvious that the results of SaNSDE+ are significantly better than that of all SGA and FEP variants. The best variants of FEP and SGA on average are FEP-5Y and SGA-10S, respectively. However, with 10^{-5} as the success fitness threshold, the best results of them are still far away from the optimum, while SaNSDE+ always found the optimum in the tested 30 independent runs. The parameter solutions that are presented in Table VI also confirm that FEP and SGA are not able to identify some of the objective parameters accurately. From the evolution curves that are presented in Fig. 7, it can be found that SGA and FEP stagnated rather

TABLE V
COMPARISON AMONG ALGORITHMS ON THE TEN-PARAMETER PROBLEM OVER 30 RUNS

	Best	Mean	Worst	Std	SR
FEP-2N	3.38e-02	7.59e-01	3.38e+00	9.30e-01	0/30
FEP-5N	3.70e-02	6.27e-01	2.88e+00	7.41e-01	0/30
FEP-10N	3.41e-02	6.03e-01	3.04e+00	8.14e-01	0/30
FEP-2Y	2.49e-02	3.86e-01	2.03e+00	6.60e-01	0/30
FEP-5Y	2.85e-02	2.33e-01	2.02e+00	3.95e-01	0/30
FEP-10Y	2.17e-02	4.67e-01	2.01e+00	6.77e-01	0/30
SGA-10S	1.49e-01	8.58e-01	2.97e+00	7.69e-01	0/30
SGA-10R	9.58e-02	9.42e-01	3.21e+00	7.97e-01	0/30
SGA-20S	2.02e-01	1.39e+00	3.34e+00	1.04e+00	0/30
SGA-20R	1.43e-01	1.14e+00	3.03e+00	8.93e-01	0/30
SaNSDE	7.16e-08	2.82e-03	4.98e-02	1.01e-02	27/30
SaNSDE+	5.40e-08	8.96e-08	1.71e-07	3.17e-08	30/30

"†" indicates that the result is significantly better than all others by the Wilcoxon rank sum test with $p < 0.001$.

TABLE VI
BEST PARAMETER SOLUTION FOUND BY ALL FEP VARIANTS (FEP-*), SGA VARIANTS (SGA-*), SANSDE, AND SANSDE+

ID/Given	FEP-*	SGA-*	SaNSDE	SaNSDE+
$x_1 / 0.13$	0.129639	0.130549	0.13	0.13
$x_2 / 0.04$	0.0391089	0.0687786	0.04	0.04
$x_3 / 0.90$	0.922775	0.530787	0.90	0.90
$x_4 / 0.90$	0.927748	0.563686	0.90	0.90
$x_5 / 0.13$	0.130192	0.129786	0.13	0.13
$x_6 / 0.13$	0.132754	0.133208	0.13	0.13
$x_7 / 0.13$	0.13014	0.12998	0.13	0.13
$x_8 / 0.04$	0.0372729	0.10196	0.0399999	0.0399999
$x_9 / 0.80$	0.856409	0.249166	0.800001	0.800001
$x_{10} / 0.90$	0.96463	0.294441	0.900001	0.900001

Optimal parameter values are given in the "Given" column.

early and made little progress thereafter, but SaNSDE+ was able to keep achieving improvements throughout the evolution process. The results of this part support the conclusion that is drawn based on benchmark functions [27] that SaNSDE+ is one of the state-of-the-art EA for numerical optimization.

Besides the final results, simplicity and the ease of use are also important issues when evaluating the practicability of an algorithm, because it is critical for the user to reobtain the reported performance. For EAs, the practicability is basically reflected by the number of control parameters and the sensitivity of EAs' performance with respect to parameter settings. It often takes

Fig. 7. Evolution curves of SGA-10S, FEP-5Y, and SaNSDE+ for the ten-parameter problem. All results have been averaged over 30 runs.

a lot of time to tune these parameters for a specific problem. Among the three compared algorithms, SaNSDE+ has the least number of parameters, i.e., two parameters NP and p . Since population size NP is a common parameter for all population based algorithms, SaNSDE+ actually has only one parameter to be predefined. Moreover, the performance of SaNSDE is not very sensitive to the parameter p , which is used to select “lpbest.” The evidence can be found by analyzing the results of SaNSDE in Table V, and Fig. 6. The only difference between SaNSDE and SaNSDE+ is that the parameter p is introduced in the latter one for selecting “lpbest.” However, the previous SaNSDE, in which the parameter p is degenerated by using the best individual as “lpbest,” still achieved much better results than all the SGA and FEP variants. The use of p is only helpful to improve the convergence speed and the ratio of successful runs of SaNSDE. For SGA, which is one of the earliest proposed EAs, has the maximum number of control parameters. All these parameters have to be tuned manually since no adaptation or self-adaptation mechanism is used to adapt them. FEP is a more advanced EA than SGA. It adopts a self-adaptive strategy to control its search step size during evolution [30]. However, the initial step size, which is problem dependent, still needs to be determined in advance. Although the performance of SGA and FEP could be improved by parameter tuning, it is still difficult for them to identify the focused building parameters correctly. In contrast, we proposed several adaptation mechanisms in SaNSDE+ to adapt almost all of its control parameters automatically, which would make it much easier for user to solve their own applications expediently.

D. Validation Using Large Dataset and Comparison With State-of-the-Art EAs

All the results that are presented in Sections V-B and V-C were achieved based on the HAMBBase simulation with 1-mo input data, which might not be sufficient to build highly reliable conclusions. The reason why we first used only 1-mo data to evaluate EAs performance is that the simulation of the HAMBBase model is computationally expensive, especially for large

TABLE VII
COMPARISON ON THE TEN-PARAMETER PROBLEM USING THE 9-MO DATASET

	FEP-5Y	SGA-10S	CLPSO	JADE	SaNSDE+
Best	1.15e-01	4.92e-01	1.38e-01	6.45e-08	1.03e-07
Median	2.51e-01	9.41e-01	2.12e-01	1.97e-01	5.73e-07
Worst	2.27e+00	3.09e+00	4.46e-01	3.87e+00	9.17e-04
Mean	3.22e-01	1.01e+00	2.57e-01	3.10e-01	7.45e-05†
Std	3.86e-01	6.73e-01	1.04e-01	6.79e-01	2.32e-04
SR	0/30	0/30	0/30	3/30	23/30

“†” indicates that the result is significantly better than all others by the Wilcoxon rank sum test with $p < 0.001$.

Fig. 8. Evolution curves of SGA-10S, FEP-5Y, and SaNSDE+ for the ten-parameter problem using the 9-mo dataset. All results have been averaged over 30 runs.

input datasets. For example, it takes about 1 week to simulate HAMBBase with the 9-mo dataset on one Intel 2.4-GHz CPU core for each run of each algorithm. Therefore, to save time, it would be good to first evaluate all the candidate EAs with small dataset, and then verify only the best ones with a sufficiently large dataset. Dataset with a size of 9 mo is often regarded as acceptable because it ensures that the building sees the two extremes of the seasonal changes [53].

Moreover, to support the claim that SaNSDE+ is efficient for such kind of problems, it may not sufficient to compare its efficacy with only classical EAs, i.e., SGA and FEP. Because in recent years EC has greatly advanced, and many new EA variants have been proposed to improve the efficacy of classical EAs. Therefore, we should further compare SaNSDE+ with some state-of-the-art EAs.

In this part, we further validated the best representatives (i.e., FEP-5Y, SGA-10S, and SaNSDE+) of the tested three kinds of EAs by using the simulation of HAMBBase with 9-mo dataset. We also compared the results with two recently proposed and highly competitive EAs in the area of global optimization. The first one is CLPSO [31], which is one of the best variants of PSO [54]. The other one is the most recently proposed DE variant, i.e., JADE [32]. Both CLPSO and JADE have been evaluated extensively using benchmark functions.

The simulation data were taken from a time period of 9 mo starting from Oct. 1, 1998. The data were also collected at discrete hourly time steps. The parameter settings of FEP-5Y, SGA-10S, and SaNSDE+ are the same as that used in

Section V-C. The parameters of CLPSO and JADE were set to the suggested values in their literature works [31] and [32]. The results of 30 independent runs are summarized in Table VII. We carried out the results in parallel by using the “Blue BEAR” cluster of the University of Birmingham.

For the results in Table VII, SaNSDE+ still outperformed FEP-5Y and SGA-10S significantly, which is consistent with the previous conclusion drawn by using 1-mo dataset. Although the newly tested CLPSO is quite stable and is better than both FEP-5Y and SGA-10S, it is still not comparable with SaNSDE+. JADE got the best fitness value among all the tested EAs. However, its success rate is very low ($SR = 3/30$), and hence, its overall performance is affected greatly.

Comparing with the results in Table V, it can be found that the performance of SaNDE+, FEP-5Y, and SGA-10S deteriorated against the increase in dataset size. This is unsurprising because we used the same number of FEs to handle a much larger dataset, for which we need to fit the building model with a longer output sequence. The situation might be different if we optimize the more difficult problem with more number of FEs. The claim can be confirmed by looking at the evolution curves in Fig. 8. It seems SaNSDE+ is not converged and still has a lot of potential to obtain better results. This also explained why the ratio of successful runs dropped from $SR = 30/30$ to $SR = 23/30$. SaNSDE+ may need more time budget to converge for the 9-mo problem. Even without increasing the number of FEs, the ratio of successful runs of SaNSDE+ is still rather high. Therefore, basically, it can be concluded that the proposed SaNSDE+ is capable of solving the parameter identification problem with large datasets as well.

VI. DISCUSSIONS AND CONCLUSION

In this paper, a study of state-of-the-art EAs, i.e., SaNSDE and SaNSDE+, as applied to a building thermal model parameter identification problem, which is typically very difficult to solve using traditional optimization methods, has been presented. Optimization problems with six and ten objective parameters were formulated based upon the HAMBBase building simulation model. A fitness function has been designed to measure the quality of identified parameter values by comparing the difference between the output of building model and that of the target building. SaNSDE+ is a new and improved variant of SaNSDE, which employs a more efficient mutation strategy to achieve a superior convergence speed.

The results that have been described in this paper suggest that the adopted EAs, especially SaNSDE+, are very effective for parameter identification problems. All the selected parameters of the building model were identified accurately. The results of SaNSDE+ are significantly better than that of two other well-known EAs, i.e., SGA and FEP.

Unfortunately, resource constraints limited this study to building simulations. In the future, we will investigate this method applied to real buildings. Once we show this method can be successfully applied, it could be integrated with existing smart energy metering services to monitor the usage of building energy for temperature regulation.

The optimization approach that has been developed in this paper is taking the building model as a black box. It should not be model dependent and is expected to work for other models as well. Therefore, extending the proposed method to such parameter identification problems in other complicated models (e.g., neural models [19]) could also be interesting future research directions.

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