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Automatic generation of energy conservation measures in buildings using genetic algorithms

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ABSTRACT

Building energy simulations are key to studying energy efficiency in buildings. The state-of-the art building energy simulation tools requires a high level of multi disciplinary domain expertise from the user and many technical data inputs that curb the usability of such programs. In this paper an IT tool is presented, which has the capability of predicting a building's energy utilization configuration based on the reported annual energy and a few non-technical inputs from the user; and correspondingly generates cost effective energy conservation measures for the intended savings.

The approach first identifies the system variables that are critical to a building's energy consumption and searches for the combination of these parameters that would give rise to the annual energy consumption as reported by the facility. Genetic algorithms are utilized to generate this database. A statistical fit is formulated between the system variables and the annual energy consumption from the database. Using this correlation, system configuration for the target energy efficiency is determined with corresponding energy conservation measures. A cost analysis is carried out to prescribe the most cost effective energy conservation measures. Competency of the tool is demonstrated in the paper through case studies on three geographies with different climate conditions.

1. Introduction

Over 40% of the energy used in most cities is used to heat or cool buildings [1]. In general energy conservation in buildings can be achieved by retrofit actions on space side (heating, cooling, lighting, window glazings, occupancy sensors, electrical equipment, lifts, escalators, cold deck temperature set point and reduced ventilation air, etc., Refs. [2–4]) or improving the efficiency of HVAC system parameters (typically improving chiller COP, condenser controls [5,6], chiller controls [7], part load efficiency [8], fan cleaning; or, appropriately sizing the equipment itself [9]). Buildings energy consumption information was reviewed in detail by Lombard et al. [10] for domestic, non-domestic and office buildings for western geographies. A list of useful tips for energy conservation for industries was provided by Bureau of Energy Efficiency, India in Ref. [11]. Rahman et al. [12] have categorized the energy conservation measures (ECMs) in buildings into three categories: major investment ECMs (variable air volume (VAV) systems against constant air volume (CAV); and low COP chillers against high COP chillers); minor investment ECMs (photo electric dimming control system against general lighting, and double glazed low emittance windows against single-glazed windows) and zero investment ECMs (reset heating and cooling set point temperatures).

In order to improve the energy efficiency of buildings, architects, building designers and facility managers require effective tools for designing, analyzing and maintaining the building energy configurations. While various ECMs are possible to realize building energy savings, only few of them may be practical, preferable, and effective. Simulating building energy consumption is therefore a key to the study of energy efficiency in buildings.

Utilization of computer codes for 'green-building' purposes have been attempted to bring in energy efficient practices into the design process [13–15] integrating the design with HVAC and control problems [16] for optimizing system operations [17], etc. Most of these attempts are confined to a design or a scheduling problem, but models/tools for complete energy analysis of an existing building which are generic in nature have not advanced owing to the difficulty and the complexity involved.

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Conventionally, building energy consumption patterns have been modeled in terms of mathematical/empirical equations which are obtained through rigorous building energy simulations. This typically involves a thorough study of the critical system parameters and their effects on the annual energy consumption (AEC). Through such studies, energy consumption as a function of these 'influences' is modeled in the form of regression equations [18] or empirical formulae. A number of statistical methods, machine learning techniques and various hygrothermal models [19,20] have been employed in this process followed by calibration techniques [21–23], sensitivity analysis [24] and so on. The exploitation of computer codes facilitated such rigorous parametric studies, which are otherwise impractical and expensive [25].

However, the choice of critical parameters is case dependent and varies on geographical issues as well. The regression equations so obtained are not generic in nature and one needs to be cautious when extending such results to another system. For example, energy consumption is highly sensitive to the efficiency and part load curves of the cooling/heating equipments. The functional fit between these variables and the energy obtained for a given system may not necessarily agree when it is being extended for another system using different HVAC systems. Lam et al. [26] have considered 28 design parameters related to building load, HVAC system and HVAC plant for a parametric study in a Hong Kong building to obtain a correlation with the predicted annual electricity consumption. Sensitivity analysis followed by linear and non-linear multiple regression techniques were used; and twelve input design parameters (six from building load, four from the HVAC system and two from the HVAC plant) were found to be the most significant design variables and were used in the energy prediction equations. Lam et al. [26] believed that the results of such study can be applied to locations that have similar climates, though no verification has been reported in the literature for any such study.

Computer technologies have also been widely employed for modeling and simulation purposes providing detailed appraisal of building energy performance. Building energy software tools directory of DOE [27] lists 392 programs that include databases, spreadsheets, component and systems analyses, and whole-building energy performance simulation programs. Modeling, simulating and analysis of thermal behavior of buildings involve multidisciplinary expertise. This fact along with the requirement of large amount of technical and physical data inputs restrict the usability of these programs.

Technical inputs such as COP of the chiller or furnace efficiency are dealt as the design intends in the design phase while these are the system performance parameters once the building is functioning and its energy efficiency is to be assessed. A facility manager may thus intend to have desired values for these parameters in the design phase while it is difficult to determine them for an existing building without practically measuring them. On the other hand, the existing state of the art computer programs demand the user to provide these data for simulating the building energy consumption and thus are not very practical. A facility manager therefore requires an energy auditor or a consultant to evaluate the energy-wise performance of a building in spite of having reasonably accurate computer programs. Another tainted advantage with such programs is that they offer the user a large number of system variables that can be tweaked; and inclusion of inaccurate values/unnecessary details into the model result in increased uncertainty [28].

There have been a number of data driven methods of energy estimation and modeling such as Black-box model [29–32], White box model [32,33] and Grey box model [32,34]. The first model is based on a regression fit between user inputs and energy consumed and typically suffers from the following common drawbacks: it is merely applicable to a given building, the input data is usually time-averaged, and system dynamism is not taken into account. The last two models are based on fundamental physics and expect the user to provide fine grained technical and non-technical data about the building, which are difficult to measure or obtain with reasonable accuracy and ease.

This paper presents an in-house tool based on a new approach that blends the black box and white box models but is different from the existing grey box models as sub metered data or finer structural inputs are not required as inputs. Although the proposed approach is still a statistical one, the user is expected to give very few obtainable inputs and the database for the regression is populated using fundamental building energy equations aided by a genetic algorithm. The objective of this tool is to automate prioritized generation of energy conservation measures which can assist the facility operators for self auditing their facilities. The tool is also desired to be simple and not time consuming to use by a non-technical facility manager.

The paper is organized as follows. Section 2 gives a detailed discussion of the tool architecture and features. Section 3 demonstrates the capability of the tool by a case study. Discussion on cost analysis of the energy conservation measures is presented in Section 4. Section 5 confines to discussions on the current limitations and way forward.

2. Our approach

The proposed tool predicts the energy performance of a functional building in terms of state of the HVAC system and the loads (thermal/lighting) based on the total energy consumption of the building, using few data inputs from the user. Building system parameters that are critically correlated with the AEC are identified and are used for building energy prediction. These parameters are varied between the probable limits and various system configurations are generated. Once the existing system configuration is predicted based on the reported AEC, system configuration corresponding to a desired energy consumption level would be evaluated and the corresponding ECMs are determined. Out of all ECMs that are possible, only few may be preferable and cost effective. Therefore at the end of the study a cost analysis is also carried out for prescribing the ECMs which are most cost effective.

2.1. Population of database

Genetic algorithms have been employed for generating various combinations of the system parameters that would result in the facility's reported annual energy consumption (target AEC). This enables a faster approach towards the target AEC within the vast search space.

For every parameter set, building energy simulation software DOE 2.2 developed at the Lawrence Berkeley Laboratory [35] has been employed for estimating the building AEC. These simulations were performed on hourly basis against day-wise granularity to minimize errors. For each combination of the parameters the building has been simulated for estimating AEC and the same, along with the parameter set, was stored in a database. This whole process has been automated. The aim of the parametric study is to generate different system scenarios for different parameter combinations, giving rise to different energy consumption values, converging towards the user defined AEC. It was observed that the genetic algorithm being employed is reasonably efficient. As the search towards the target AEC progressed, it has generated successful cases that meet the prescribed indoor comfort needs, avoiding the generation of cases that would have inferior fitness values and/or without indoor comfort being met.

From all the generated cases, those cases in which the simulated energy matched the target AEC by 1% were considered for further processing. Upon logical filtering of these cases, the scenario that has a close match with the target AEC was chosen to replicate the configuration of the building under study.

Based on the database being generated, a nonlinear regression correlation between the system variables and the AEC has been formulated. Subsequently, a system configuration corresponding to a target energy level (with desired savings) has been determined from this regression fit. In this study, 10% savings in the total AEC were intended and the corresponding ECMs with respect to the given AEC have been determined and presented in this paper.

2.2. DOE 2.2 engine

DOE 2.2 is an up-to-date, computer program that simulates the hourly energy usage of a building given hourly weather information and a description of the building and its HVAC equipment [35]. It requires an input text file featuring all the necessary parameters and details that describe the building and its systems; and readable by DOE 2.2. It has a subprogram called 'Building description language (BDL) processor' for translation of inputs, and four simulation subprograms: LOADS, SYSTEMS, PLANT and ECON to calculate the energy loads, evaluate the HVAC system and plant performance and to calculate the economics respectively. The BDL processor reads the input data and calculates the response factors (physical-civil-thermal details) for the transient heat flow in walls and weighting factors for the thermal response of building spaces. The LOADS simulation subprogram calculates the sensible and latent components of the hourly heating or cooling load for maintaining each zone of the building at the set temperature. The SYSTEMS subprogram assesses the secondary systems (e.g. air handling units) while PLANT evaluates the primary systems and thereby estimates the fuel and electrical demands of the building.

A baseline input file has been created and the same was altered by varying the parameters for generating different cases. Each time the file was tweaked, the DOE 2.2 engine was called and the case has been simulated. In addition to the input file, DOE 2.2 also requires meteorological data pertaining to the selected geography. The weather files were obtained from DOE's website [36] and fed to the program.

In each simulation, the input file was processed in DOE 2.2, system loads were computed, the HVAC plant and its systems were simulated, zone wise temperatures and the total electricity and total natural gas consumptions were calculated; and an output file was created. The input and output of each simulated case were stored in a database.

In each case, the zone temperature was read from the output file and compared with the user defined comfort temperature limits. If the comfort level is met, the case was tagged with comfort = 1. It was comfort = 0 otherwise.

2.3. Genetic algorithms

As mentioned in the previous sections, nine control variables have been identified to correlate with the building energy (electricity plus natural gas) consumption and the zone temperature for maintaining comfort. The fitness function was defined accordingly, in terms of three parameters representing total electricity, total natural gas consumption and comfort in the following way:

$$\text{fitness function}: \quad F = a \times F_e + b \times F_n \tag{1}$$

where

$$F_e = 1 - \left(\frac{|\text{used electricity} - \text{calculate electricity}|}{\text{used electricity}} \right)$$

$$F_n = 1 - \left(\frac{|\text{used natural gas} - \text{calculate natural gas}|}{\text{used natural gas}} \right)$$

'a' and 'b' are the coefficients whose values depend on the respective fitness components and the comfort in such a way that:

$a = 4$	when $F_e \geq 0.99$ and comfort = 1
$a = 2$	when $F_e \geq 0.99$ and comfort = 0
$a = 1$	when $F_e < 0.99$ and comfort = 1
$a = 0.5$	when $F_e < 0.99$ and comfort = 0
$b = 4$	when $F_n \geq 0.99$ and comfort = 1
$b = 2$	when $F_n \geq 0.99$ and comfort = 0
$b = 1$	when $F_n < 0.99$ and comfort = 1
$b = 0.5$	when $F_n < 0.99$ and comfort = 0

Therefore the maximum value of the fitness function thus defined is 8; and the vectors with best fitness values would have AEC value close to the target AEC and indoor comfort met. These vectors were given priority in the evolution of the chromosomes by assigning them the higher weights. The following steps are involved in the algorithm:

- *Initialization of population*: A set of randomized population is generated with each variable, given a value in its permissible limits.
- *Starting the DOE 2.2 engine*: For each of the randomly generated vectors, the DOE 2.2 engine is run; and the value of the fitness function is determined.
- *Evaluation of the chromosomes*: Best fit vectors are those which have a maximum value of 'F'. Generations are populated using crossover and mutation concepts.
  a. *Crossover*: Best vectors would have a greater probability of reproducing themselves. By crossing two input vectors, two other new vectors are generated for the next generation. The crossover rate chosen in the present study was 0.9.
  b. *Mutation*: In order to determine the global maxima of the fitness function, certain components of the vectors are randomly changed. The mutation rate specified was 0.1.
  c. *Stopping criteria*: From all the cases generated, those in which the calculated energy is close to the target (user) AEC by 1% were considered for further processing. Correspondingly, the fitness value should be 7.92 at the least. Once this condition is surpassed, the improvement in the solution for successive generations is observed. If the fitness value does not improve by 0.5% for three successive generations, meaning that the solution has already matured within the algorithm's capabilities, the algorithm is stopped. It was observed that ideally the algorithm should converge at a solution within 2 h time; or 3 h maximum. Hence 3 h was set as the time limit.

Flow chart of the methodology is shown in Fig. 1.

3. Case studies

This section presents three case studies in which a model building is simulated for three geographies.

Initially, a building scenario (assumed to be user system) with known values of the critical parameters (referred to as base case) is simulated for the building energy. This energy is specified to

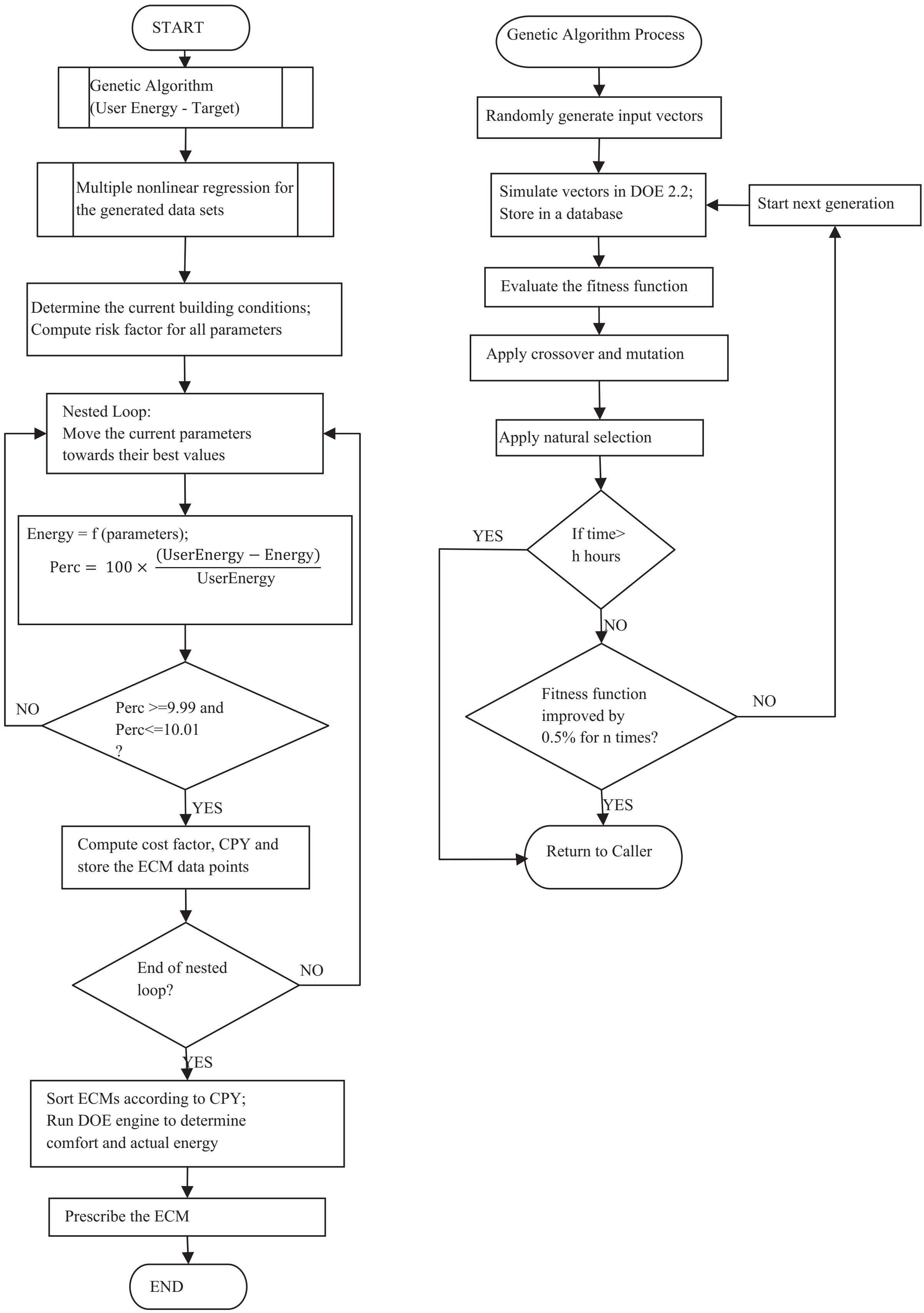

Fig. 1. Flow chart for the proposed methodology.

Table 1
Description of building parameters.

Variable name	Value
Lighting power (W/m^2)	10.75
Equipment load (W/m^2)	9.4
Chiller size (kW)	351.6 (Chennai) 263.7 (Baltimore) 70.32 (Juneau)
Heater size (kW)	0 (Chennai) 761.8 (Baltimore) 843.8 (Juneau)
Absorptance of roof	0.6
Absorptance of exterior wall	0.6
Absorptance of interior wall	0.7
Absorptance of floor	0.7
Absorptance of window frame	0.7
Absorptance of door	0.7
Shading coefficient	0
U value of roof (W/m^2 K)	0.043
U value of exterior wall (W/m^2 K)	0.080
U value of interior wall (W/m^2 K)	0.514
U value of floor (W/m^2 K)	0.028
Conductance of the window frame (W/m^2 K)	4.87
Conductance of the door (W/m^2 K)	5.39
Infiltration flow ($m^3/s\,m^2$)	0.0000437

the code as the target and the code is run to determine the values of the critical variables that would result in this target energy. The competency of the code in predicting the respective values close to the ones initially considered is assessed. The results are presented for three geographies: viz. Chennai, TN-India (hot and humid), Baltimore, MD-USA (composite) and Juneau, AK-USA (cold and humid continental) to illustrate the generality of the approach and its applicability to different climate conditions across the globe.

3.1. Description of building parameters

The model building under the study is a single-storey–single-zone office building with a total area of 3721 m^2 (61 m × 61 m). Total height of the building is 3.6 m and the floor to ceiling height is 2.7 m. Each of the four walls has a glass door of 3.78 m^2 (1.8 m × 2.1 m) at the center and two windows of 34.6 m^2 (23.1 m × 1.5 m) each on either side of the door. The HVAC system being considered is a constant volume – packaged single zone system with DX coils and a natural gas furnace as cooling and heating equipment respectively. For the calculation of total annual energy consumption (AEC), units of total natural gas consumed (in therms) have been converted to equivalent kWh and added to the kWh of total electricity being consumed. The number of people is assumed to be 250. Cooling and heating set points at which chiller and heater get activated are 76 °F and 73 °F respectively. Building occupancy starts from 08:00 h, peaks by 09:00 h and ends by 19:00 h. The operation of chiller, heater and AHU fans is scheduled from 07:00 h to 20:00 h. The economizer set point is 66 °F. Table 1 summarizes the other descriptions of the building. Only these data are expected from the user in addition to the annual energy consumption as inputs to the tool. Obtaining these inputs is straightforward and would not involve any field measurements.

Table 2 shows the list of parameters that are critically correlated with the AEC and hence they have been used for the building energy prediction. These parameters were varied between the probable limits and various system configurations have been generated.

Table 2
Critical system parameters.

Variable	Description	Min	Max
ARPE	Area per person (m^2/person)	4.64	18.58
CFM	Circulating air flow (m^3/s)	15.8	22.4
OA	Outside air flow per person (m^3/s person)	0.007	0.016
TMIN	Minimum supply temperature (°F)	55	70
TMAX	Maximum supply temperature (°F)	95	120
BF	Bypass factor of the DX coils	0.1	0.5
EIR	Electric input ratio of chiller (=1/COP)	0.2	0.5
SUPEF	Supply fan efficiency	0.5	0.7
ECON	Economizer limit (°F)	65	70

Upper and lower limits of CFM were dynamically determined by the program based on the chiller capacity and built-up area of the building. A packaged single zone HVAC system with DX coil unit was considered for the building. The three case studies are discussed in the following sections.

3.1.1. Chennai, TN-India (hot and humid)

The assumed values of the system variables for the model building are shown in Table 3. The system's AEC was simulated using DOE 2.2 for Chennai climate; and it was 449,489 kWh. This AEC has been specified to the code as the target and genetic algorithms were run to generate various scenarios that would result in AECs closer to the specified value. The closest value of the AEC, as determined by the code was 448,984 kWh; and the associated parameter values are presented in Table 3 in comparison with the baseline reference values.

All the cases, in which the AEC close to the target (449,489 kWh) by 1% and the indoor comfort being met (2307 cases) have been considered to obtaining a regression fit between AEC and the system variables being considered.

Initially, each parameter has been independently varied and the nature of its relation (linear/quadratic/cubic) with respect to the AEC was observed. A multiple nonlinear regression fit was then formulated considering all the variables and their natures. Several regression functions have been tested and the final regression model was selected based on the accuracy (R^2 value of the fit and the standard deviation) and ease of use (in terms of simplicity and interpretability). The nonlinear regression equation thus obtained is as follows:

$$\begin{aligned}[AEC]_{elec} = \; & 255,745\,BF^3 - 247,823\,BF^2 + 112,582\,BF + 7,432,299\,EIR + 848.94\,CFM + 67\,ECON^2 \\ & -9288\,ECON - 257\,TMIN^2 + 31,735\,TMIN - 162,969,670\,OA^2 + 8,112,766\,OA \\ & +54,953\,SUPEF^2 - 142,164\,SUPEF - 436,772 \end{aligned} \quad (2)$$

(R^2 = 0.989, standard error = 4119.5).

For the sample 2307 data cases, error between the energy as simulated by DOE 2.2 and that predicted from Eq. (2) has been calculated. Fig. 2 shows the distribution of such errors among the

Table 3
System configurations: Chennai, TN-India.

System	Baseline	GA
TMIN (°F)	60	60
TMAX (°F)	–	–
CFM (m^3/s)	19.6	19.57
BF	0.195	0.15
EIR	0.25	0.26
HIR	–	–
SUPEF	0.56	0.59
OA (m^3/s person)	0.011	0.0102
ECON (°F)	66	66
$[AEC]_{elec}$ (kWh)	449,489	448,984
$[AEC]_{ngas}$ (kWh)	–	–
AEC (kWh)	449,489	448,984

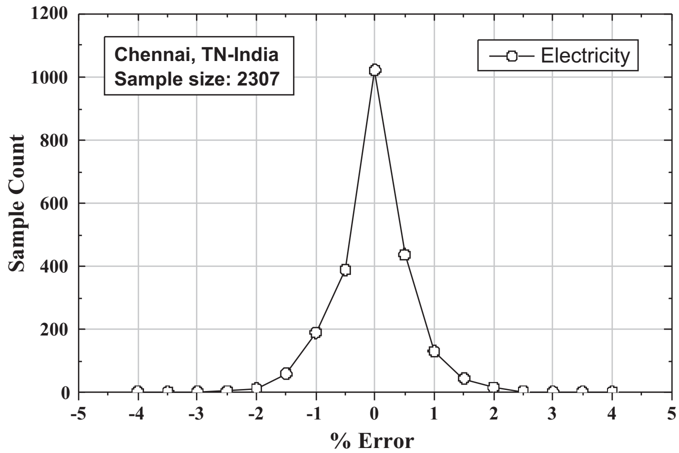

Fig. 2. Error distribution (Chennai case).

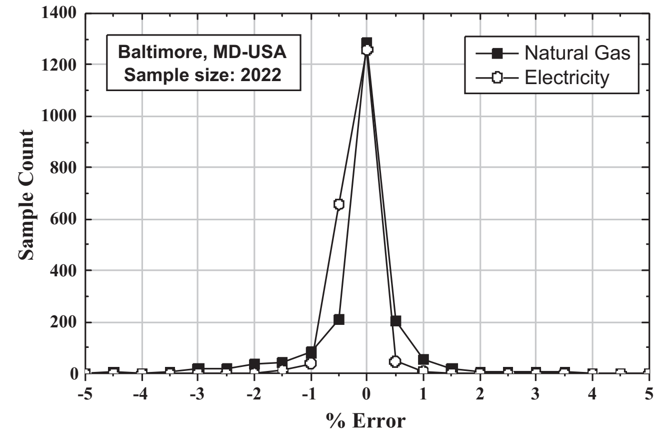

Fig. 3. Error distribution (Baltimore case).

sample datasets. It can be observed that about 80% of the samples have near-zero errors validating the reliability of the regression model.

3.1.2. Baltimore, MD-USA (composite)

Table 4 shows the assumed values of the system variables for the model building and the system's AEC (299,834 kWh of electricity and 208,294 kWh of natural gas), as determined from DOE 2.2 simulations for Baltimore climate. These respective values of AEC have been specified to the code as the targets and genetic algorithms were run to generate various scenarios that would result in AECs close to these values. The closest values of the respective AECs, as determined by the code were 299,758 kWh of electricity and 207,121 kWh of natural gas. Table 4 shows these details along with the associated parameter values in comparison with the baseline system's values.

Individual multiple nonlinear regression fits have been obtained for both annual electricity consumption and natural gas consumption in a similar manner as explained in the previous section; and are presented in the following equations:

For the sample of 2022 data cases, errors between the electricity consumption and the natural gas consumption as simulated by DOE 2.2 and those predicted from Eq. (3) and (4) have been calculated and presented in Fig. 3. It can be observed that about 97% (electricity) and 84% (natural gas) of the samples have near-zero errors validating the reliability of the regression model.

3.1.3. Juneau, AK-USA (cold and humid continental)

The assumed values of the system variables for the model building and the system's AEC (262,322 kWh of electricity and 475,451 kWh of natural gas), as determined from DOE 2.2 simulations for Juneau climate are shown in Table 5. The closest values of the respective AECs, as obtained from the genetic algorithm code were 260,392 kWh of electricity and 477,941 kWh of natural gas respectively. Table 5 shows these details along with the associated parameter values in comparison with the baseline system's values.

Individual multiple nonlinear regression fits have been obtained for both annual electricity consumption and natural gas consumption in a similar manner as explained in the previous section; and are presented in the following equations:

$$\begin{aligned}[\mathrm{AEC}]_{\mathrm{elec}} = {} & 88,143\,\mathrm{BF}^3 - 63,027\,\mathrm{BF}^2 + 21,704\,\mathrm{BF} + 146,389\,\mathrm{EIR} + 1413\,\mathrm{CFM} - 42\,\mathrm{ECON}^2 \\ & + 4809\,\mathrm{ECON} - 84\,\mathrm{TMIN}^2 + 10,530\,\mathrm{TMIN} - 13,580,806\,\mathrm{OA}^2 + 717,021\,\mathrm{OA} \\ & + 129,896\,\mathrm{SUPEF}^2 - 220,929\,\mathrm{SUPEF} - 153,046\end{aligned} \tag{3}$$

(R^2 = 0.984, standard error = 1575.7)

$$\begin{aligned}[\mathrm{AEC}]_{\mathrm{ngas}} = {} & -1309\,\mathrm{CFM} + 13,839,574\,\mathrm{OA} - 84,296\,\mathrm{SUPEF}^2 + 140,376\,\mathrm{SUPEF} - 1.846\,\mathrm{TMAX}^2 \\ & + 439.5\,\mathrm{TMAX} + 147,818\,\mathrm{HIR} - 214,564\end{aligned} \tag{4}$$

(R^2 = 0.993, standard error = 1934).

Table 4
System configurations: Baltimore, MD-USA.

System	Baseline	GA
TMIN (°F)	60	60
TMAX (°F)	110	112
CFM (m^3/s)	19.6	19.43
BF	0.195	0.21
EIR	0.25	0.27
HIR	1.4	1.43
SUPEF	0.56	0.59
OA (m^3/s person)	0.011	0.0112
ECON (°F)	66	67
$[\mathrm{AEC}]_{\mathrm{elec}}$ (kWh)	299,834	299,758
$[\mathrm{AEC}]_{\mathrm{ngas}}$ (kWh)	208,294	207,121
AEC (kWh)	508,128	506,879

Table 5
System configurations: Juneau, AK-USA.

System	Baseline	GA
TMIN (°F)	60	58
TMAX (°F)	110	109
CFM (m^3/s)	19.6	20.18
BF	0.195	0.2
EIR	0.25	0.31
HIR	1.4	1.52
SUPEF	0.56	0.61
OA (m^3/s person)	0.011	0.0102
ECON (°F)	66	65
$[\mathrm{AEC}]_{\mathrm{elec}}$ (kWh)	262,322	260,392
$[\mathrm{AEC}]_{\mathrm{ngas}}$ (kWh)	475,451	477,942
AEC (kWh)	737,773	738,334

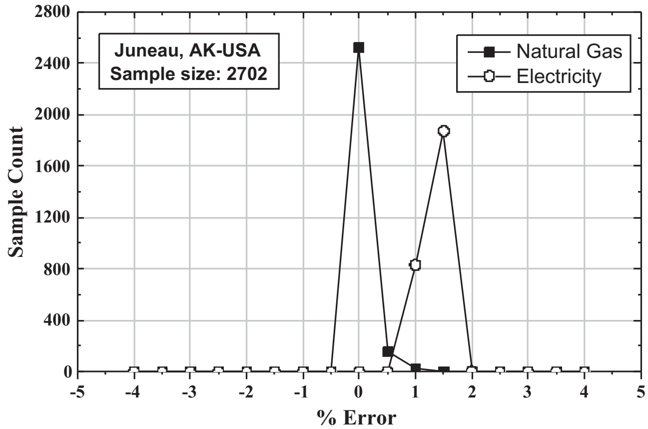

Fig. 4. Error distribution (Juneau case).

$$[AEC]_{elec} = 5409\,BF^3 - 4081\,BF^2 + 1064\,BF + 1770\,EIR + 1834\,CFM + 0.738\,ECON^2 - 196\,ECON + TMIN^2 + TMIN + 2,064,282\,OA^2 - 59,574\,OA + 97,475\,SUPEF^2 - 178,869\,SUPEF + 305,345 \quad (5)$$

(R^2 = 0.995, standard error = 4282)

$$[AEC]_{ngas} = -2307\,CFM + 27,242,766\,OA + 47,935\,SUPEF^2 + 28,099\,SUPEF - 4.454\,TMAX^2 + 1113\,TMAX + 336,481\,HIR - 370,176 \quad (6)$$

(R^2 = 0.993, standard error = 3164).

Errors between the electricity consumption and the natural gas consumption as simulated by DOE 2.2 and those predicted from Eqs. (5) and (6) have been calculated and presented in Fig. 4 for all the 2702 data samples. All the points lie within 1–2% error region in the calculation of the electricity consumption; and 99% of the samples have near-zero errors in the calculation of natural gas consumption.

4. Generation of ECMs

All the system variables being set at their optimum values would refer to the most energy efficient configuration of the system. This configuration, on the other hand, may possibly refer to the most expensive system. Once the current system configuration is predicted, the regression functions are used to determine the system's configuration that would result in the intended savings and correspondingly determine the ECMs.

It was found that 8431 ECMs for Chennai, 75,851 ECMs for Baltimore and 152,305 ECMs for Juneau are possible for 10% energy savings. These ECMs pertain to a range of improvements in various system variables. The tool carries out a cost analysis for each of such ECMs to determine their cost effectiveness.

4.1. Cost analysis

A cost per year (CPY) function is defined in which the total cost involved in performing a particular ECM is divided by the life time (in years) of that ECM: the time for which the intended improvements are viable.

For a given ECM that involves improvements in 'n' system parameters, the cost per year (CPY) function is defined as:

$$CPY = \sum_{x=1}^{n} \left(\frac{M_x}{T_x}\right)(C_x + R_x) \quad (7)$$

where C is the normalized cost factor (Figs. 5–8) involved in executing the particular improvement in the corresponding variable.

This cost factor includes the capital cost, operational and maintenance costs. Hypothetical cost factor curves for the variables EIR, HIR, BF and SUPEF are shown in Figs. 5–8. Other variables have no cost factors as any ECM pertaining to those variables would merely imply to reset the system controls that do not involve any cost. Cost factor is obtained by normalizing the total cost with the maximum (M) cost, so that the factor takes values between 0 and 1. Each cost curve consists of two elements: (a) cost involved in improving the existing system and (b) cost involved in changing the system to another (better) system. The latter case arises for the fact that a given equipment type cannot be improved beyond a certain limit and demands change of system.

Each step in these curves represents the cost involved for improving the existing system; and moving from one step to another step refers to a change of system. T is the time (in years)

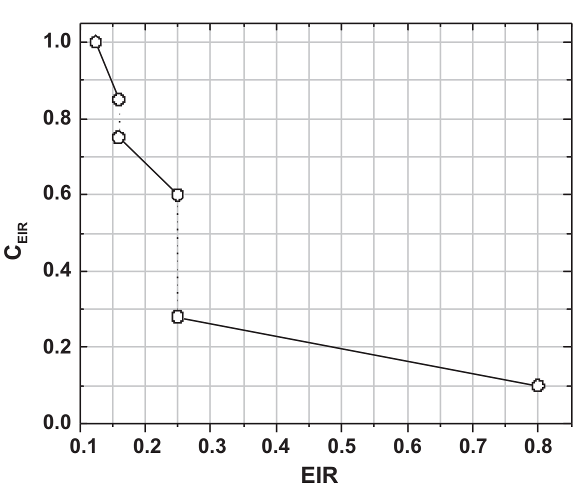

Fig. 5. Cost factor for EIR.

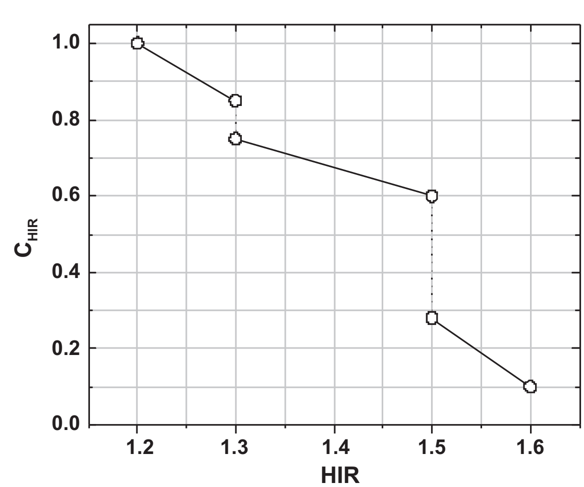

Fig. 6. Cost factor for HIR.

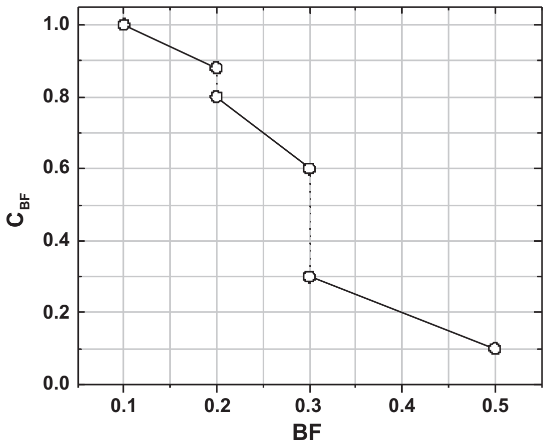

Fig. 7. Cost factor for BF.

for which the predicted energy savings are foreseen corresponding to a particular variable improvement.

If prediction of a variable value representing the existing system is erroneous, R is the risk cost (per year) involved in executing the particular improvement in that variable and is estimated as shown in Eq. (8).

$$R_x = \frac{\Delta \mathrm{AEC}_x}{\text{target energy savings}} \quad (8)$$

The factor (M/T) takes an 8:8:4:1 proportion for EIR, HIR, BF and SUPEF variables respectively. This is estimated based on their typical total cost per project life estimations. The factor (M/T) for the other variables (having zero cost factor) is taken as 1 as those variables do have non-zero risk factors.

For all the possible ECMs, the CPY function has been evaluated and the ECMs are accordingly sorted out in the order of least cost. The case pertaining to the most cost effective ECM has been simulated in DOE 2.2 to confirm the space comfort and the desired (10%) energy savings that were essentially predicted by the regression equation. The final ECMs are prescribed accordingly.

The system configurations corresponding to the most cost effective ECMs as determined by the tool for the respective cases are shown in Table 6 in comparison with the baseline case.

5. Limitations and way forward

The tool is still under development in terms of its usability over various building/HVAC system types. The tool can currently handle single zone systems using packaged HVAC systems: DX coils for cooling and furnace (fueled by natural gas) or electric heating equipment types. Applicability of the tool would be extended to more complex systems such as multi zone, multiple zone, variable air volume systems etc. with a variety of chiller/heater types in the future. Some of the difficulties in doing so are: (a) complexity of the building description (input) file grows with the system complexity; with multiple zone systems: each zone needs to be modeled individually; (b) too many system parameters will bring in challenges in utilizing genetic algorithms, as well as in obtaining their functional relationship with AEC; (c) cost curves and risk factors should be practical, so they must be standardized for a more reliable selection of ECMs.

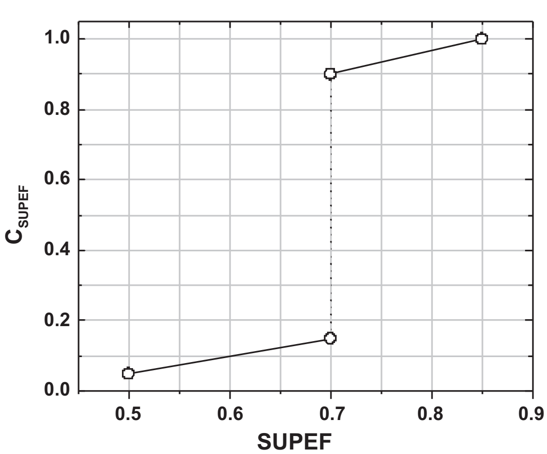

Fig. 8. Cost factor for SUPEF.

Table 6
System configurations: ECMs.

System	10% savings			
	Baseline	Chennai	Baltimore	Juneau
TMIN (°F)	60	66	60	58
TMAX (°F)	110	–	103	99
CFM (m^3/s)	19.6	18.66	18.66	18.66
BF	0.195	0.19	0.21	0.2
EIR	0.25	0.23	0.27	0.31
HIR	1.4	–	1.2	1.29
SUPEF	0.56	0.68	0.59	0.61
OA (m^3/s person)	0.011	0.0084	0.0102	0.0102
ECON (°F)	66	70	69	65
$[\mathrm{AEC}]_{\mathrm{elec}}$ (kWh)				
Chennai	449,489	403,784	N/A	N/A
Baltimore	299,834	N/A	297,000	N/A
Juneau	262,322	N/A	N/A	258,138
$[\mathrm{AEC}]_{\mathrm{ngas}}$ (kWh)				
Chennai	–	–	N/A	N/A
Baltimore	208,294	N/A	163,904	N/A
Juneau	475,451	N/A	N/A	401,351
AEC (kWh)				
Chennai	449,489	403,784	N/A	N/A
Baltimore	508,128	N/A	460,904	N/A
Juneau	737,773	N/A	N/A	659,489

6. Summary and conclusions

An IT tool has been presented, which has the capability of predicting a given building's energy consumption configuration based on the reported annual energy and a few non-technical inputs from the user; and correspondingly generates cost effective energy conservation measures for the intended savings.

The present approach first identifies the building system variables that are critically correlated with the building energy consumption and populates large number of combinations of these parameters. For each of such combinations, building energy is simulated for location-specific weather data. System configuration that would result in the facility's reported annual energy consumption is then determined. Genetic algorithms are utilized to generate such database. From the database, a nonlinear regression fit between the system variables and the annual energy consumption is formulated. Using the regression fit, system configuration for the target energy efficiency is determined, with corresponding energy conservation measures. After a cost analysis, the cost effective energy conservation measures are prescribed. Competency of the tool has been successfully demonstrated in the paper through case studies on three geographies with different climate conditions.

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