KNN & SENSITIVITY ANALYSIS AS AN INTEGRATED APPROACH FOR CALIBRATION OF BUILDING ENERGY MODELS FOR RETROFIT

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ABSTRACT

This paper reports on a practical process that evaluates retrofit technology for zero carbon performance where calibration outcome is used to quantify uncertainty in building performance prediction before and after retrofit.

This process is performed in two phases. The first phase is to develop and calibrate the model before retrofitting. This model is used to design the parameters for retrofit. Moreover, it identifies the most sensitive parameters, and whether or not they are physically observable. In the second phase, we update the model to include all retrofit improvements done to the property and perform further calibration since the model can incorporate further uncertainties caused by retrofit improvements. This allows us to understand if the calibrated model generated before retrofit still applies after retrofit. This paper seeks to discuss the development of the first phase of the process. The buildings under analysis are semi-detached houses belonging to Birmingham City Council in the UK.

Detailed monitored data, such as internal and external air temperature, solar radiation, gas and electricity consumption are used to calibrate the model before and after the retrofit. For calibration, we use K Nearest Neighbour (KNN) to conduct parameter sensitivity analysis with the aim to fine tune the model and establish one-to-ne relationship between the simulated and actual building performance.

A case study is presented where the annual electricity and gas consumption predicted by jEPlus+EA (uses EnergyPlus as core engine) was within 1% of the actual energy consumption of the buildings. This was achieved after three iterations over the base case model.

INTRODUCTION

In this study, Retrofit improvements are carried out by installing a TCosy envelope developed by our industrial partner in the retrofit project Beattie Passive, including windows and doors, integrated mechanical ventilation and heat recovery system, all to Passivhaus standard. TCosy provides deep retrofit frame solution creating a void from foundations to roof; encapsulating the existing roof and external brickwork (Beattie Passive, 2016). The void is subsequently injected with insulation to give a highly efficient building envelope with no thermal bridges, and it greatly enhances the U-value of the walls and roof.

Until now, TCosy system developed by Beattie Passive has been based on an on-site 'stick construction' delivered over a period of 8+ weeks. The aim of this study is to facilitate transformation of the retrofit method from the on-site to off-site manufacturing. The off-site manufacturing will involve the manufacture and assembly of the panels, integrated MVHR system within the panels including couplings and dampeners. Passivhaus certified windows would also be fitted as integral part of the envelope. To design the retrofit using TCosy system, various parameter values need to be identified to allow the highest possible performance in terms of energy consumption and thermal comfort. These parameters include envelope depth and insulation type. Hence, dynamic simulation model is developed, using the drawings and specifications obtained from a detailed house survey, to be subsequently used for design of the retrofit.

Whole building energy simulation tools are becoming an integral part of design and optimisation of buildings. Building simulation can compare various energy conservation measures, in the form of theoretical extensions or refinements to the input model, to reduce the consumption of energy in a building, as well as assessing various performance optimisation measures during operational stage. However, actual building performance varies from predicted building performance calculated via building simulation model. Disagreement between simulated and monitored energy consumption is a common issue in building simulation, and is known as a performance gap. Hence, model calibration is needed to close the gap between the model and actual building performance.

Related work

Despite the wide use of calibration, no universal and consensus calibration guidelines exist yet. According to (Monetti et al., 2015) Mean Bias Error (MBE) and the Coefficient of Variation of the Root Mean Square Error (Cv(RMSE)) are used for validating a calibrated model by measuring the goodness-of-fit of the building energy model (ASHRAE, 2002). The authors of (Fabrizio et al., 2015) have reviewed a wide range of calibration methods, the study concluded that most applications still use trial-error approaches. Even though new applications of calibration are being performed, trial-error methods remain the most frequently employed. These are semi-manual approaches to model calibration, and they generally rely on manual pragmatic user intervention to 'fine-tune' individual parameters to achieve a calibrated solution. In order to improve the reproducibility, all previous calibrated models are stored in version control repository as supporting evidence to understand the assumptions made. However, trial-error methods can be time consuming, and require detailed information about the existing building , which may not be available. Furthermore, entire calibration process should be automated to ensure efficiency and consistency (Tahmasebi, 2012).

However, automated approaches employ analytical tools or techniques to assist in the calibration process, while employing mathematical and statistical techniques to reach their goal. For example, Monetti et al, (2015), performed calibration using EnergyPlus and GenOpt optimisation function to optimise influencing parameters and improve the correspondence to the measured values. The optimisation process terminated when a model with minimum performance gap was found. All solutions resulted from the calibration process were post processed for evaluating the model accuracy, where the MBE and the Cv(RMSE) are used for this purpose. Further optimisation runs were performed while varying the model parameters at each run to find better results. However, Monetti et al (2015) do not fully explain the mechanism for varying the parameter values during calibration.

Another calibration approach is based on the NSGA-II algorithm Basurra et al. (2015) and Jankovic and Basurra (2016). In a typical optimisation analysis, the usual aim is to search for the optimum performance points. However, when using NSGA-II for calibration, the aim is to locate the performance points of the simulation model that are the closest to the actual performance. These performance points are then used to find out the corresponding model parameters that result in the smallest performance gap. NSGA-II has a built in crowding distance function to estimate density of dominant solutions around the optimal solutions.

Calibrating a model can be a complex task as the user has to decide which of the inputs must be changed in order to reduce the gap between measurements and predictions. According to Clarke (1993), three aspects have been identified to this issue. First, the input parameters that may be in error must be selected, or a deficiency in the simulation model should be removed. Secondly, the process for adjusting the model parameters to minimise the performance gap should be automated. Finally, the expertise of the user is a significant factor in both cases.

This issue has been addressed in this paper by using iterative and automatic calculation of parameter inputs for fine-tuning between predicted and actual building performance. We use KNN algorithm and density avoidance technique to determine appropriate values for the parameter set in order to minimise residuals. Parameter tuning is performed using sensitivity analysis for the following advantages described by Pannell (1997); 1- increase understanding of the relationship between input and output variables; 2- model simplification – by fixing the inputs that have no effect on the output; 3- finding regions in the space of input factors for which the model output is either maximum or minimum or meets some optimum criterion. Another important objective of this paper is to present a simplified methodology to be used by professionals as well as by researchers, for the calibration of dynamic building energy models.

METHODOLOGY

k-nearest neighbours' algorithm (KNN) have been used in a wide range of research areas such as Computer vision, Data mining and Pattern recognition. KNN is a simple approach to find the most k of the nearest neighbours of some instance in a dataset.

KNN is non-parametric. This means that KNN works without presumption of the primary data distribution. Thus, the simulation requires no post-training on the dataset. This is useful for calibration in building simulation as it is widely accepted that predicted energy consumption differ from metered energy consumption. There are various reasons for this deviation in performance, for example, the effect of thermal bridging, degradation of building materials, airtightness and occupancy behaviour. In this study, we use the method proposed by Basurra et al. (2015), which uses KNN with density avoidance method for model calibration. However, we perform sensitivity analysis with multiple iterations of calibration for model simplification, and to achieve minimal performance gap.

KNN is used for classification by locating the nearest neighbour in instance space and labelling the unknown instance with the same class label as that of the located known neighbour. A popular approach for classification process in KNN is to use nearest neighbours by calculating inverse distance and majority voting. This allows neighbours at K > 1 to decide the class labelling. One way to implement this is to use the Euclidean function, which calculates the distance between two points in the solution space. That is given $x = (x_1, \dots, x_n)$ and $y = (y_1, \dots, y_n)$, the distance is calculated as

$$d_E(x, y) = \sqrt{\sum_{n=1}^{N} (x_n - y_n)^2}. \quad (1)$$

The algorithm function

k is the number of nearest neighbours in the solution space $S := (p_1, \ldots, p_n)$ where p_n is the solution sample in the form $p_1 = (x_i, c_i)$, where x_i solution entry with all parameter values of the point p_i. c_i is the class that p_i belongs to (see Figure 1).

- Start:
    - For each $\boldsymbol{p}' = (\boldsymbol{x}', \boldsymbol{c}')$
    - Calculate the distanced $\boldsymbol{d}(\boldsymbol{x}', \boldsymbol{x}_i)$ between $\boldsymbol{p}'$ and all $\boldsymbol{p}_i$ belonging to $\boldsymbol{S}$
    - Re-organise all $\boldsymbol{p}_i$ in accordance to their distance
    - Select the first $\boldsymbol{k}$ points from the sorted list, those are the $\boldsymbol{k}$ closest training samples to $\boldsymbol{p}'$
    - Allocate a class to $\boldsymbol{p}'$ based on majority vote: $\boldsymbol{c}' = \boldsymbol{argmaxy}\sum(\boldsymbol{x}_i, \boldsymbol{c}_i)$ belonging to $\boldsymbol{S}$, $\boldsymbol{I}(\boldsymbol{y} = \boldsymbol{c}_i)$. For $\boldsymbol{p}_i$, where $_i$ 1,2, .. number of pints in $\boldsymbol{c}_i$
- End:

Figure 1: KNN algorithm steps

The selection of k is critical. This is because a small value of k means that the results will be increasingly influenced by noise. However, a large value of k can make it computationally expensive, but also defeats the concept behind the KNN that solution 'points' that are near are likely to have similar densities/classes. One simple approach suggested by Richard et al. (2000) is to set k as $k = \sqrt{n}$ where n is the total number of points in the solution space.

For the purpose of calibration of building models, KNN is used to identify neighbour solutions scattered around a reference point, hence covering all regions in the solution space. This allows identifying all possible parameter values responsible for generating close by solutions to the reference point. However, if the reference point is located nearby a highly densely populated area of solutions, the KNN will blindly select all those solutions even if some/all contain the same parameter values, hence, density estimation techniques are used to overcome this challenge. For example, Parzen-window classification (Richard et al, 2000) is a technique for nonparametric density estimation. It estimates a probability density function *p(x)* for a specific point *p(x)* from a sample *p(xn)* that doesn't require any knowledge or assumption about the underlying distribution. To estimate density with Parzen-window at a point *x*, a circle is placed at the centre of x and keep increasing its size until k neighbours are captured. The density estimation uses the following formulae:

$$p(x) = \frac{k/n}{a} \qquad (2)$$

In the formula above, *n* is the total solutions, and *a* is the area of the circle. The numerator is constant and the density is influenced by its value. Unlike KNN which selects the k nearest neighbours and labelling them with the weighted majority of its neighbours' votes, Parzen-window assign the solutions weight by means of the density function.

We use similar technique to density estimation in KNN and Parzen-window, but instead of using density to classify neighbours, we use density calculation to select a fewer neighbours located in high-density areas in the solution space. Hence, using the KNN with the aid of density avoidance the algorithm will include other nearby solutions positioned in sparse areas, which may include different parameter values that could match closely with the actual building behaviour.

Density avoidance for KNN

In Basurra et al., (2015) we proposed a density avoidance algorithm, which has been tested in various scenarios for the purpose of model calibration. Our proposed density avoidance algorithm is briefly explained below.

Starting from a close by solution from the reference point, each solution will form a circular region with a constant radius R to capture all surrounding nodes in the solution space. For example, let us consider a solution *X* of *N* solutions in a dataset. *X* will perform the density estimation and calculate the density using Equation (2).

If density is above a threshold, the node closest to *X* (not the reference point), will be tagged as high-density node (HD). The whole process repeats again, and *X* becomes the second closest node to the reference point. In subsequent iterations, HD nodes are not selected to perform the density calculation, and will not be considered in the density check if they fall within the range within a circle area of another valid low-density node. Following these rules, all nodes in the solution space will be tagged as either HD or none.
Then we implement the KNN algorithm that selects the closest k neighbours, but also selects only those that are not HD solutions. This was successfully implemented, and algorithm pseudocode describing the steps is shown in Figure 2.

- PROGRAM DensityExclusionAlgorithm:
    - Using **KNN**, CALCULATE distances to all ***N*** solutions from Reference Point.
    - Store the ***N*** neighbours with their distances in a list ***L***
    - Sort list ***L*** in a ascendant order putting least distant solutions at the top of ***L***.
    - LOOP through ***L*** starting from the top, and select ***X*** solution
    - ***X*** Identify nearby neighbours from N using a predefined radius ***R***, and store them in a new list $\boldsymbol{L}_2$.
        - ***X*** calculates density $\boldsymbol{L}_2$
    - If ($Density > Threshold$ && $N \neq HD$)
        - THEN from $\boldsymbol{L}_2$, set "HD" to Neighbour closest to ***X***
            - ELSE DO NOTHING;
    - ENDLOOP
    - CALCULATE neighbours of Reference Point with ***K*** number of neighbours.
- End

Figure 2: Pseudocode describing the steps of the density avoidance algorithm.

pre-calibration procedureTo test this new approach, Birmingham City Council provided two semi-detached properties for the field trials, and these two properties will be referred as A and B. Detailed survey of the properties was carried out to establish construction types and dimensions, and to create CAD drawings. 3D laser scanning was carried out on the external surface of the properties to facilitate off-site measurements and identify any obstacles that might affect retrofit such as drainpipes, security lights etc. (See Figure 3).

Dynamic simulation model was developed, using the drawings and specifications obtained from the survey, to be subsequently used for design of the retrofit (See Figure 4). Hence, calibration is essential at this stage to ensure that building thermal performance is represented accurately. During the calibration process, the input values of the model parameters are varied and tested, with the aim to fine-tune the model performance, until the simulated model matches the performance of the actual building.

Table 1 below shows the parameters used to calibrate the model. Variations of significant design parameters were identified during the detailed survey to represent uncertainties in the model, but also as critical inputs that exert significant influence on the model's output. Through the iterative calibration stages, design parameters were repeatedly adjusted to determine optimum configuration, tuning the model to run with a realistic range of operating conditions. These input variables shown in Table 1 identified 3840 solution combinations.

Figure 3: Point cloud of the filed trial properties A and B.

From the survey conducted on the properties A and B, however, to simplify the calibration process, we used house A model for simulation while treating house B as adjacent building (See Figure 4). Energy bills show that house A annual consumption was 9108000 kJ of electricity and 43842600 kJ of gas over 2015-2016. We used these results to form a reference point in the solution space.

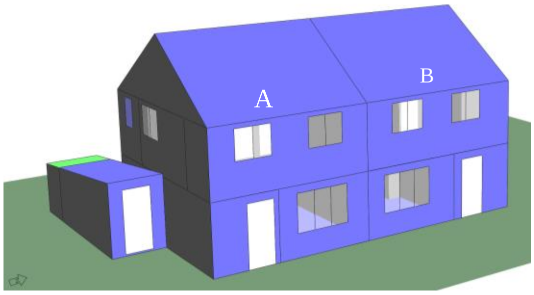

Figure 4: Model was constructed in IES (IES, 2016) and was later exported in .idf format to run on JEPlus-EA

The calibration process for this case study was performed in three iterative refinement stages. The aim of each stage was to calibrate the model further in order to establish a nearly one-to-one relationship between the simulated and actual data.

RESULTS

1st stage of calibration

For optimisation during 1st stage of calibration, KNN with density avoidance algorithm was implemented on the optimisation output of this stage as shown in Figure 5 and its zoomed-in version Figure 6. Table 2 shows the calibrated design variables. Each row representing a combination of parameter values was identified by KNN as neighbouring solutions shown as red dots in Figures 5 and 6. The solution rows in Table 2 are organised by distance from the reference point shown as a blue diagonal cross in the solution space. Hence, the first row consists of the design variables of the best calibrated model that was identified during the 1st stages of calibration.

After performing sensitivity analysis, it is apparent that the parameter *Air Changes Per Hour* has the same value 3.0 (ac/h) in all design solutions, hence it was flagged as the least sensitive parameter of this calibration stage. To simplify the model, this parameter was fixed at 3.0 (ac/h) as it has no effect on the outputs. This not only helped in fine-tuning the model, but it also minimised the number of jobs required to complete the simulation and optimisation in the 2nd calibration stage. This is because KNN eliminated all values (1.0, 3.0, 5.0, 7.0, 9.0) used for the 1st collaboration stage, which existed in solutions positioned far away from the reference point, shown as grey dots in Figure 5 and 6.

Table 1: Optimisation / parametric analysis settings used for the building model during 1st stage of calibration

Parameter	Value for each step		Parameter	Value for each step
Lighting density (W/m2)	3.0, 4.0, 5.0, 6.0, 7.0, 8.0		Set Temperature Other Areas (°C)	15, 16, 17, 18
Misc. Electrical Heat Gains	3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.		Air Changes Per Hour	1.0, 3.0, 5.0, 7.0, 9.0
Set Temperature Lounge °C	16, 17, 18, 19		**Total number of Jobs 3840**	

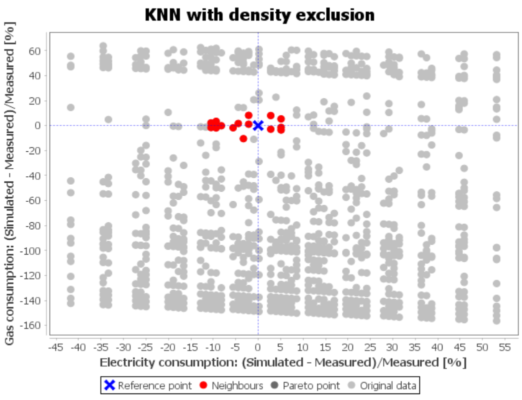

Figure 5: KNN in operation while using the density avoidance algorithm on the output of the 1st stage calibration

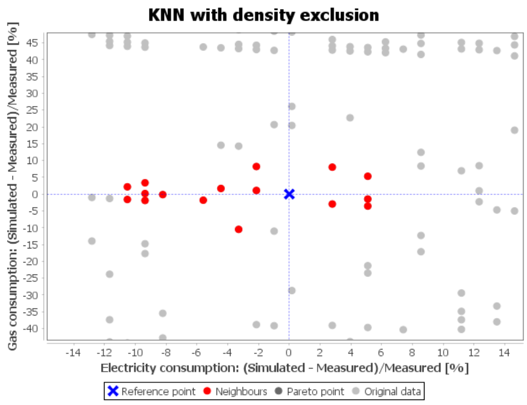

Figure 6: Zoomed-in version of Figure 5. KNN in operation while using the density avoidance algorithm on the output of the 1st stage calibration

Table 2: Detailed parametric settings of the K neighbour solutions, displayed in Red in Figures 5 and 6, which were generated from the 1st stage of calibration process. Table rows are sorted in ascending order by the distance from the reference point.

Lighting Power Density	Misc. Electrical Heat Gains	Set Temperature Lounge (°C)	Set Temperature Other Areas (°C)	Air Changes Per Hour	Electricity consumption	Gas consumption
6	7	17	18	3	-2.137868711	1.089426651
3	9	19	18	3	2.794348539	-2.940217932
4	9	17	18	3	-4.442053223	1.679406742
5	7	18	18	3	5.098533052	-1.459878745
3	10	19	18	3	-5.59414548	-1.816311971
5	7	19	17	3	5.098533052	5.301777868
6	7	18	17	3	-2.137868711	8.207465069

2nd stage of calibration

In the second stage of calibration we re-run the same model with JEPlus+EA, while fixing the insensitive parameter *Air Changes Per Hour* at 3.0 ac/h. In Table 2, it is clear that the outcome design value range for *Lighting Density*, *Electrical Heat Gains*, *Set Temperature Lounge* and *Set Temperature Other Areas* are considerably smaller than the original set of values used in the 1st stage of calibration. These parameters vary in their sensitivities as they consist of an average of four distinct values as shown in Table 2, but clearly the second worst parameter in terms of sensitivity is the parameter *Set Temperature Other Areas.* As it consists of only two values, 17 and 18, these were fixed in the 3rd stage of calibration. In the previous study Basurra et al. (2015), we used the maximum and minimum output value for each sensitive parameter to break the range further into smaller steps to be used as inputs for subsequent simulations. This is to bring the simulation model closer to the reference point.

This approach is not ideal in this case study as the difference between the minimum and maximum values was considerable for some parameters. To resolve this issue, we had to deal with each output value separately. For example, if the range is $(x_0,\ x_1,\ x_2,\ \dots x_n)$, for x_n two new input values $'x_1$ and $''x_1$ were generated to surround x_1 in the new input range. Hence the new input range to be used for the subsequent calibration was $(x_0, 'x_1,\ x_1, ''x_1, x_2, \dots)$. The following two equations were used to calculate $'x_1$ and $''x_1$;

$$'x_1 = \frac{x_n - x_{n-1}}{2} \dots, \qquad x_{n-1} < 'x_n < x_n \qquad (2)$$

$$''x_1 = \frac{x_{n+1} - x_n}{2} \dots, \qquad x_n < ''x_n < x_{n+1} \qquad (3)$$

let us consider the value of 4 in the parameter range of Lighting Power Density in Table 2. Since the difference between 4 and the next and previous values in the range equals to 1, using the equations above, the new input values to be used for fine tuning in 2nd stage of calibration were 3.5, 4, 4.5. These are shown in Table 3. Note, the total number of simulation jobs required for 2nd stage of calibration is 672, which is considerably smaller than 3840 jobs executed during the 1st stage of calibration.

Table 3: Optimisation / parametric analysis settings used for the building model during 2nd stage of calibration

Parameter	Value for each step		Parameter	Value for each step
Lighting density(W/m2)	3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5		Set Temperature Other Areas (°C)	17, 18
Misc. Electrical Heat Gains	6.5, 7.0, 7.5, 8.5, 9.0, 9.5		Air Changes Per Hour	3.0
Set Temperature Lounge (°C)	15.5, 16, 16.5, 17, 17.5, 19, 19.5		**Total number of Jobs 672**	

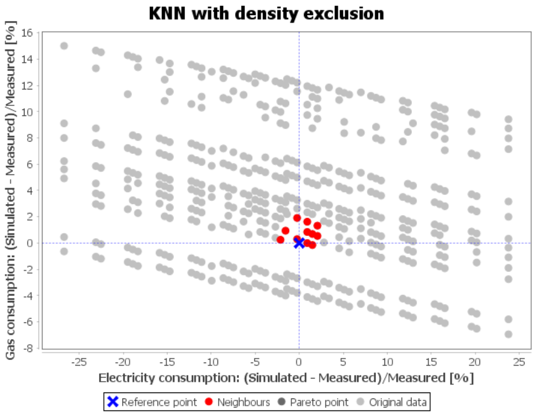

Figure 7: KNN in operation while using the density avoidance algorithm on the output of the 2nd stage calibration

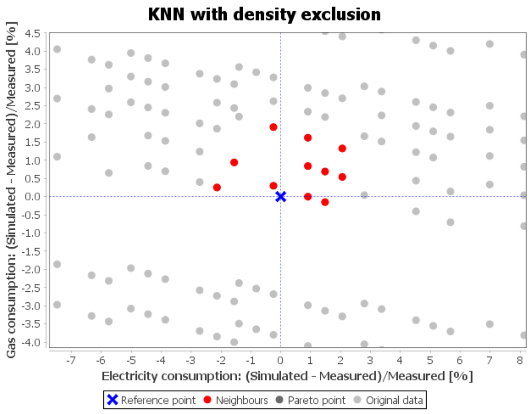

Figure 8: Zoomed-in version of Figure 7. KNN in operation while using the density avoidance algorithm on the output of the 2nd stage calibration

Table 4: Detailed parametric settings of the K neighbour solutions, displayed in Red in Figures 7 and 8, which were generated from the 2nd stage of calibration process. Table rows are sorted in ascending order by the distance from the reference point.

Lighting density	Misc. Electrical Heat Gains	Set Temperature Lounge (°C)	Set Temperature Other Areas (°C)	Air Changes Per Hour	Electricity consumption	Gas consumption
4	8.5	17.5	18	3	-0.247806214	0.297004736
5	7.5	17.5	18	3	0.904286042	-0.00108236
5	7.5	17	18	3	0.904286042	0.839523666
5.5	7	17.5	18	3	1.48033217	-0.151131264
5.5	7	17	18	3	1.48033217	0.690602897
6.5	6.5	17	18	3	-1.561822583	0.940296697
5	7.5	16.5	18	3	0.904286042	1.618843338

3rd stage calibration

From the output of the 2nd stage of calibration, it is clear that the solutions shown in the Figure 7 and 8 are closer to the reference point than the design solutions resulted from the 1st stage of calibration. Also, the value range for each parameter is smaller. Note that the parameter *Set Temperature Other Areas* shown in Table 4 has now one value fixed value of 18. By fixing *Set Temperature Other Areas* and *Air Changes Per Hour* at the values 3 and 18 respectively, and by breaking the values of the remaining parameters into smaller steps as performed in the 2nd stage of calibration using Equations 2 and 3, we can perform the 3rd stage of calibration using only 360 simulation jobs. All parameter input values are included in the Table 5.

After applying KNN and density avoidance algorithm to the output shown in Figures 9 and 10, it is apparent that all neighbour solutions are much closer than before in comparison to pervious stages of calibration. Now, all neighbouring solutions shown in Table 6 have the uncertainty rate of less than 1% and the best solution so far is 0.12 % for electricity consumption and 0.1% for gas consumption. Hence, the single-row table below is the best model to represent the actual building behaviour consists of the corresponding parameter values. Further calibrations can be performed to achieve even closer results if desirable.

Lighting density	Misc. Electrical Heat Gains	Set Temperature Lounge (°C)	Set Temperature Other Areas (°C)	Air Changes Per Hour
6.3	6.5	17.5	18	3

Table 5: Optimisation / parametric analysis settings used for the building model during 3rd stage of calibration

Parameter	Value for each step	Parameter	Value for each step
Lighting density(W/m2)	3.8,4.0,4.5,5.0, 5.3, 5.8, 6.0, 6.3	Set Temperature Other Areas (°C)	18
Misc. Electrical Heat Gains	6.25, 6.5, 6.8, 7.25, 7.5, 7.8, 8.25 8.5, 8.8	Air Changes Per Hour	3
Set Temperature Lounge (°C)	16.8, 17, 17.25, 17.5, 17.8	**Total number of Jobs 360**	

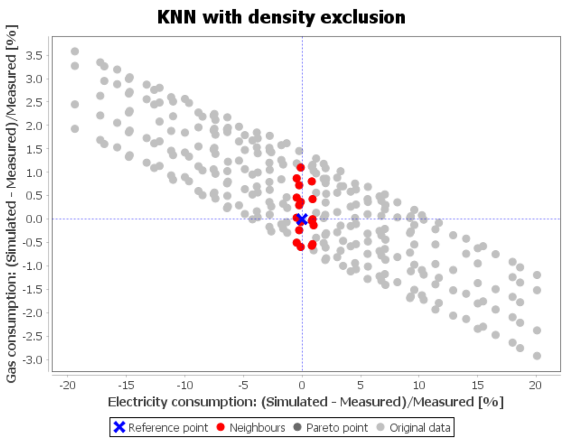

Figure 9: KNN in operation while using the density avoidance algorithm on the output of the 3rd stage calibration.

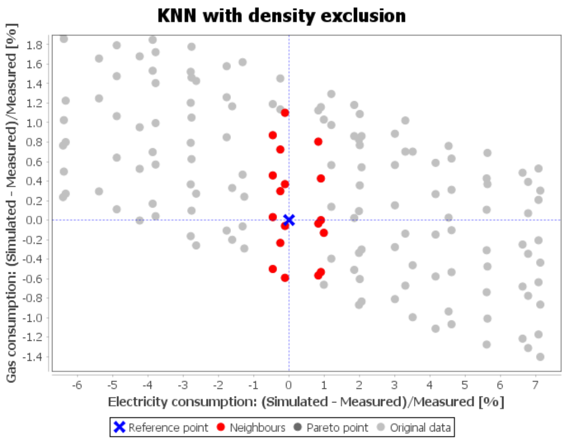

Figure 10: Zoomed-in version of Figure 9. KNN in operation while using the density avoidance algorithm on the output of the 3rd stage calibration. process

Table 6: Detailed parametric settings of the K neighbour solutions, displayed in Red in Figures 9 and 10, which were generated from the 3rd stage of calibration process. Table rows are sorted in ascending order by the distance from the reference point.

lighting density	Misc. Electrical Heat Gains	Set Temperature Lounge (°C)	Set Temperature Other Areas (°C)	Air Changes Per Hour	Electricity consumption	Gas consumption
6.3	6.5	17.5	18	3	-0.11454223	-0.060317236
4	8.5	17.8	18	3	-0.247806214	-0.234343735
6.3	6.5	17.25	18	3	-0.11454223	0.368165171
4	8.5	17.5	18	3	-0.247806214	0.297004736
6	6.8	17.5	18	3	-0.460169907	0.030155561
6.3	6.5	17.8	18	3	-0.11454223	-0.592944361
6	6.8	17.25	18	3	-0.460169907	0.458149188

DISCUSSION

We compared the use of KNN and sensitivity analysis approach with NSGA-II algorithm with the built in crowding distance function discussed above and presented in the study by Basurra et al. (2015) and Jankovic and Basurra (2016). It was concluded that NSGA-II is easier to use and require less time to generate the results. This is because KNN requires post processing, and if further calibration refinement is required, more optimisation iterations should be carried out. However, KNN with the density avoidance technique outperforms NSGA-II as it identifies neighbour solutions that are close to the reference point, as well as considering those solutions that scattered evenly in the solution space while covering different regions on the graph.

Another advantage of using KNN when combined with sensitivity analysis is that it helps identifying most and least influential parameters. Hence, when the former are fixed and the latter are broken further into smaller steps to be used as input values for subsequent simulations, the solutions becomes considerably closer to the reference point.

To prove our concept, we used NSGA-II to calibrate the same model and the same parameter range used at 1st stage of calibration shown in Table 1 (Jankovic and Basurra, 2016). The best result generated from running optimisation was 0.17% of uncertainty for electricity consumption and 0.33% for gas consumption. That is slightly lower in accuracy than the best calibrated design solution obtained from this study. To lower the model uncertainty in NSGA-II, trial-error method should be performed, which hugely depends on user’s assumptions and experience. Even then, some design solutions are likely to be missed, as NSGA-II provides solutions that only exist in the positive quadrant of the solution space.

CONCLUSIONS AND FUTURE WORK

As simulation tools become more widely used as the basis of future design tools for new built and retrofit, the need for calibration methodologies will grow (Van de Perre et al 1991). Such methodologies ensure that, at least in a limited number of cases, there are acceptable candidates to provide reasonable prediction of energy performance of existing buildings. Various studies suggest that calibration is still largely performed on the bases of trial-error approaches, which depends on user's assumptions and experience. Even for an experienced modeller, trial-error approaches could be labour intensive and time consuming. Hence, the use of automated methods allow experts and non experts to perform calibration effectively by preventing the manual tuning of each parameter, but also swiftly speeding the time required for calibration.

A case study is presented in this paper where the annual electricity and gas consumption predicted by the use of KNN and sensitivity analysis, using JEPLus+EA, running EnergyPlus as its simulation engine, was lower by less than 1% than the actual value. The calibration was obtained after three iterations over the base model. The building under the consideration was a semi detached house belonging to Birmingham City Council. Using the identified calibrated design solutions with the least error ratio, we can predict with some certainty the optimal thickness of the retrofit envelope in terms of thermal comfort, energy consumption and retrofit cost. This has been studied in more depth by Jankovic and Basurra (2016). In the second phase, and when the actual retrofit is completed, we will update the calibrated model to include all retrofit improvements in the property and perform further calibration to incorporate further uncertainties caused by retrofit improvements. This will allow us to understand if the calibrated model generated before retrofit still applies after retrofit.

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