3. Theoretical background.

Initially, this section will justify and elaborate on general concepts which are fundamental to the chosen CCM methodology. Subsequently, it will provide specific details for the two contrasting CCM programs used in this report and finally details of the methods used in the investigation.

3.1. Iteration scheme.

A fundamental aspect of CCM based on RCNs is the solution method. The state-space representation of an RCN must be iteratively evaluated over the input time series to produce the output time series (e.g. an internal temperature profile). One option is to use the analytic solution to the forced state response of RCNs, which is given by Equation 9 [29].

$$x(t) = e^{At} \cdot x(0) + \int_0^t e^{A\cdot(t-\tau)} \times B \cdot u(\tau) \cdot d\tau \qquad \textbf{Equation 9}$$

Where, τ – system time constant.

However, in this case the input time series is discretised. Therefore, the discrete time form of the analytic solution is required, which is given by Equation 10.

$$x_{(n+1)} = e^{A\cdot Ts} \cdot x_{(n)} + A^{-1} \cdot [e^{A\cdot Ts} - I] \cdot B \cdot u_{(n)} \qquad \textbf{Equation 10}$$

Where, Ts – time-step size and n – time-step number

An alternative option is to use one of the many numeric solutions available, the simplest of which is given by Equation 11.

$$x_{(n+1)} = x_{(n)} + \left(A \cdot x_{(n)} + B \cdot u_{(n)}\right) \cdot Ts \qquad \textbf{Equation 11}$$

Although the analytic solution is the most accurate, time constraints meant that it could not be implemented in this report, so the numeric solution was used instead. The only potential exceptions to this rule are the pre-scripted MATLAB functions such as “Greyest” [30] or “Lsim” [31] , which may internally use the analytic solution.

Knowing that using the numerical solution may cause inaccuracies, the time step of all estimation and input data series was reduced to just 5 minutes in an attempt to compensate.

3.2. Initial parameter approximation.

The central task of the CCM programs in this report is to determine the best RCN parameters to model a particular building structure. In all cases, the system parameters will ultimately be identified using ML. However, the CCM process is more efficient if accurate parameter approximations are created at the start. Doing this:

- Reduces the computation time required for ML.
- Allows one parameter to be fixed, thus reducing the spread of possible optimal solutions for ML.
- Allows validation of the parameters identified using ML.

Equations 5 & 6 are typically used to determine RCN parameters analytically. However, to combine material properties into construction properties, and then construction properties into RCN parameters, it is also necessary to use Equations 12, 13, and 14.

$$\mathrm{R_{Series}} = \mathrm{R_1} + \mathrm{R_2} + \mathrm{R_N}$$ **Equation 12**

$$\mathrm{R_{Parrallel}} = \left(\frac{1}{\mathrm{R_1}} + \frac{1}{\mathrm{R_N}}\right)^{-1}$$ **Equation 13**

$$\mathrm{C_{Sum}} = \mathrm{C_1} + \mathrm{C_2} + \mathrm{C_N}$$ **Equation 14**

3.3. Re-parameterisation [28].

Non-linear effects such as radiation, convection and seasonal changes mean the best RCN parameter values fluctuate. Re-evaluating the RCN parameters on a regular basis partially compensates for this variation, thus improving the “fit” of the system output data to the estimation data. Re-parameterisation also reduces the amount of information each set of RCN parameters represents. This enables the determination of RCN parameters which better model specific periods of data. However, re-parameterisation is time intensive and increases the possibility that the model will become over fitted, so it should be used sparingly.

3.4. Parameterisation scheme.

The two most commonly used parameterisation methodologies in the literature are G-BMs and GAs. G-BMs take a starting point in the problem space (an n-dimensional space where every possible solution exists) and iteratively improve it. The optimality of a particular point in the problem space is defined by the objective function. When no point neighbouring the current point has a greater optimality, the process ends. GAs (also known as direct search) generate a random set of points and evaluate their optimality using the objective function. The process repeats with a marginally more selective set of random points based on the most optimal point from the previous generation. When no points in the set are more optimal than the most optimal point from the previous generation, the process ends. The key characteristics of both methods are given by Table 2.

Characteristics of G-BMs and GAs [32]	
G-BMs	**GAs**
Efficient/fast.	Inefficient/slow.
Results strongly depend on starting point.	Results weakly depend on the starting point.
Require continuous objective functions.	Accept non-continuous objective functions.

Table 2

Table 2 does not conclusively support one method over the other. Furthermore, there are hybrid methods which complicate the problem of selection further. Consequently, it was decided to differentiate the methods by trialling the following incarnations of each method using a basic CCM program and a simple test structure.

- MATLAB's Greyest function (G-BM).
- MATLAB's GA [33] function (Hybrid).

3.4.1. Trial of Greyest (G-BM).

MATLAB's Greyest function was used successfully in the literature [23] to parameterise RCNs; so, it was decided to try and apply it in this report. The following key setting were used in the trial:

- Search method: trust-region-reflective algorithm using the least squares method.
- Initial system: state is treated as an independent estimation parameter.
- Fit metric: normalized root-mean-square deviation (nRMSD).
- Re-parameterisation: never, seasonally, monthly and daily.

The average fit accuracy value of the resulting fit, ~258%, is very poor, and a measure of the problems of using Greyest for this application.

- Firstly, Greyest does not output the time varying series for all state variables, only output variables. This makes applying re-parameterisation properly more challenging, because without knowing the values of the states it is impossible to ensure continuity.

- Secondly, uses Kalman Filtering [34] to improve the model output for a specific training period. However, in this report Kalman Filtering is an unnecessary intrusion into the parameter estimation process. With Kalman Filtering disabled, the fit accuracy values were even worse.
- Thirdly, the average internal air temperature model tends to drop to 0°C only to instantly reset at the beginning of the next parameterisation period.

Greyest is fundamentally incompatible with re-parameterisation. Still, its poor performance remains unaccounted for. One possibility is that the results of Greyest are strongly dependent on the starting point, and the parameter approximations it was fed were too poor. Nonetheless, it could not be made to work in this report.

3.4.2. Trial of the GA (Hybrid).

There are multiple examples of GAs in the literature [21, 28]. Actually, MATLAB's GA is a hybrid function; it begins with a GA component, then when a certain convergence limit is reached it switches to a G-BM. The key settings used in the trial were as follows:

- Search method: 'fmincon', which seeks to minimise a penalty function whilst obeying the constraints placed on the system parameters.
- Initial system state: the initial state is treated as an independent estimation parameter or extracted from system data depending on the context.
- Fit metric: Normalized root-mean-square deviation (nRMSD).
- Re-parameterisation: never, seasonally, monthly and daily.

MATLAB's GA was validated by an excellent average fit accuracy value of ~74%. The strength of the result also validates the MATLAB script written to support re-parameterisation when using MATLAB's GA. Also, because the state variables are easily accessible, the states can made consistent across re-parameterisation steps, rather than being re-evaluated each time. The weakest aspect of the fit produced using MATLAB's GA is the daily temperature fluctuation, which is poor compared to the yearly fluctuation.

Based on these trials MATLAB's GA will be used in in this report. This is because it produced the best results and operates in the most transparent way. A potential avenue of research would be to compare these parameterisation methods more rigorously.

3.5. *“CCM Program 1”.*

3.5.1. *RCN structure*

CCM Program 1 is designed to be simple; it is conceived as limit of acceptable functionality [24]. In keeping with this, CCM Program 1 incorporates the most basic RCN intended model whole building structures found in the literature [23] (shown in Figure 1).

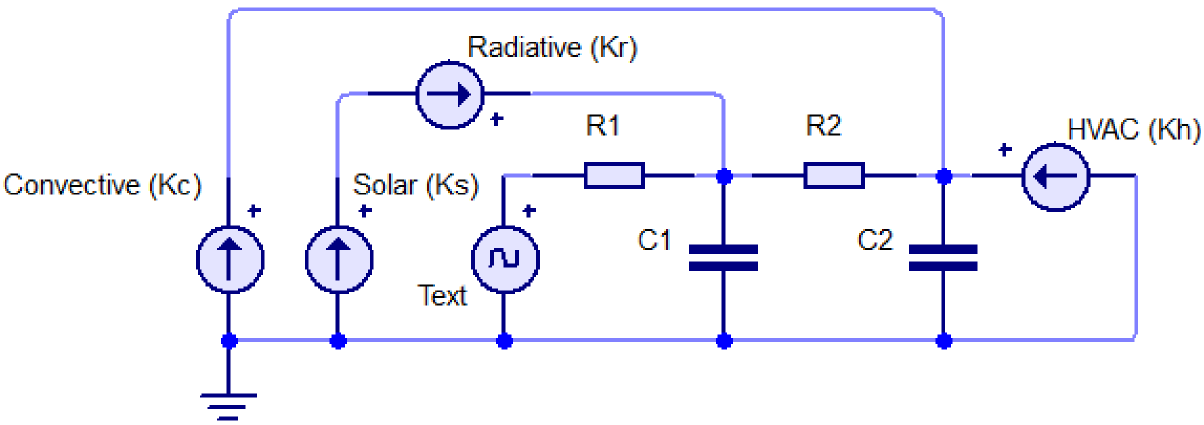


Figure 1

In RCN in Figure 1 models any building as one thermal zone (C2), separated from the external environment by a single all-encompassing building envelope (R1, R2 and C1). There is no regard for the actual complexity of the building structure. As with all RCNs, the A and C state-space system matrices (Equation 3) define both type (“RCN1”) and the fundamental dynamics. For Figure 1 these matrices are provided below.

- $A = \begin{bmatrix} -\frac{R1+R2}{C1*R1*R2} & \frac{1}{C1*R2} \\ \frac{1}{C2*R2} & -\frac{1}{C2*R2} \end{bmatrix};$
- $C = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix};$

As the RCN type has been defined, the full structure of state-space representation depends only on the B and D matrices (Equation 4), which indicate the number and positioning of gains (system inputs). For Figure 1 these matrices are provided below.

- $B = \begin{bmatrix} \frac{1}{R1*C1} & \frac{Ks}{C1} & \frac{Kr}{C1} & 0 & 0 \\ 0 & 0 & 0 & \frac{Kc}{C2} & \frac{Kh}{C2} \end{bmatrix};$
- $D = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$

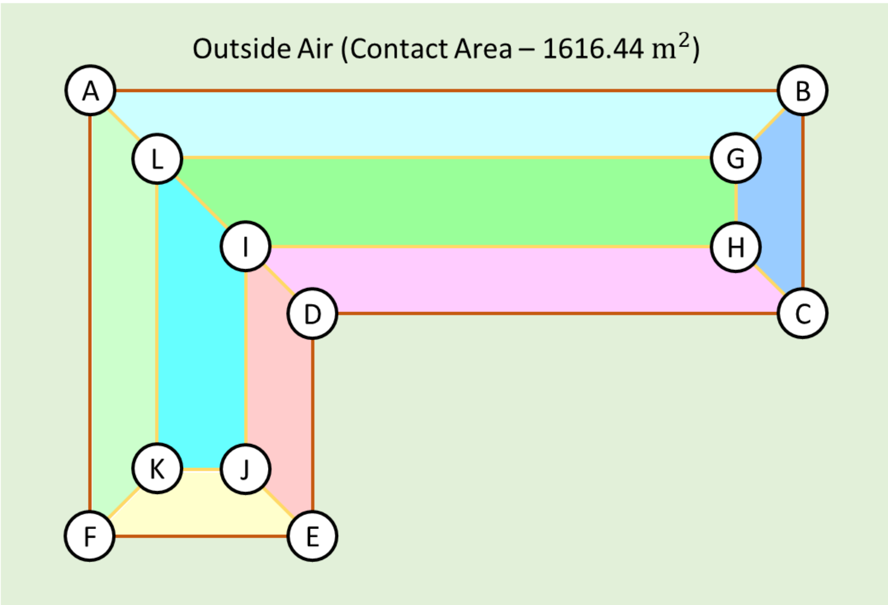
For extra clarity the time dependent vectors $\vec{x}$, $\dot{\vec{x}}$ and $\vec{u}$ which represent the system states and the system inputs are also provided.

- $\vec{x} = \begin{bmatrix} T_{C1} \\ T_{C2} \end{bmatrix}$; $\dot{\vec{x}} = \begin{bmatrix} \dot{T}_{C1} \\ \dot{T}_{C2} \end{bmatrix}$; $\vec{u} = \begin{bmatrix} T_{ext} \\ q_{Ks} \\ q_{Kr} \\ q_{Kc} \\ q_{Kh} \end{bmatrix}$;

3.5.2. Test building-structure/ estimation and input data.

The source of estimation and input data for CCM Program was an EnergyPlus model called “LBuilding-G000” found in the “EnergyPlusV8-9-0\ExampleFiles” directory (shown in Figure 2). Advantages of using BPS (in the form of EnergyPlus) to generate estimation and input data include:

- Synthesising infinite data.
- Access to a comprehensive list of simulation variables.
- Control of the complexity of the BPS model to keep in step with the CCM method.



Surface	Length (m)
B-G, C-H, D-I, E-J, F-K, A-L	6.47
B-C, D-E, E-F, I-J	15.24
C-D, H-I	33.53
G-H, J-K	6.09
A-B	48.77
G-L	39.62
A-F	30.48
K-L	21.33
I-L	8.61

Surface	Construction
	IntWallConstruction
	FaceBrkIns4LWConcBlkGyp_R-17 / WinLib_2003
Ceiling	SlagFeltIns6LWConcGapAcoTile_R-21
Floor	BotFloorConstruction

Figure 2

As shown in Figure 2, LBuilding-G000 has multiple thermal zones. Consequently, the estimation and input data from EnergyPlus was formatted as shown in Table 3, with many quantities specified for each thermal zone.

				ZONE_A_B_G_L						ZONE_B_C_H_G
Date/Time	Outdoor Air Temperature [C]	Direct Solar Radiation [W/m2]	Diffuse Solar Radiation [W/m2]	Total Internal Radiant Heating Energy [J]	Total Internal Visible Radiation Heating Energy [J]	Total Internal Convective Heating Energy [J]	Air Temperature [C]	Sensible Heating Energy [J]	Sensible Cooling Energy [J]	
01/01 01:00:00	14.1	0	0	383563	103267	799912	19.4	0	0	E.c.t.
01/01 02:00:00	15.9	0	0	383587	103267	800006	19.3	0	0	
01/01 03:00:00	15.8	0	0	383644	103267	800233	19.3	0	0	

Table 3

The estimation data is a full set of internal air temperature values for each thermal zone. These values are volume averaged to produce a single average internal air temperature value. The input data includes external air temperature and solar gains for the whole structure. It also has radiative heating energy, convective heating energy and HVAC heating energy for each time-step and thermal zone.

3.5.3. Initial RCN parameter estimation.

Using the analytic methods discussed previously, along with the structural information provided in Figure 2 and the material properties included in the EnergyPlus file, the RCN parameters for LBuilding-G000 were estimated.

- $\mathrm{R1} + \mathrm{R2} \sim 7.599 \times 10^{-5}$ [K/W]
- $\mathrm{C1} \sim 5.155 \times 10^{8}$ [J/K]
- $\mathrm{C2} \sim 1.778 \times 10^{6}$ [J/K]

3.5.4. HVAC details.

The HVAC system in LBuilding-G000 is based on a gas boiler and controlled ventilation. The distribution system, which is displayed in Figure 3, is identical for each thermal zone.

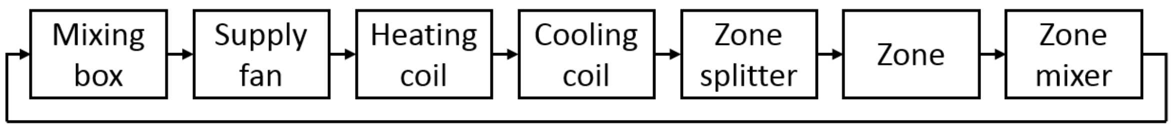


Figure 3

The consequence of this layout is that in RCN1, HVAC gains are treated as a convective.

3.6. "CCM Program 2".

3.6.1. RCN structure

CCM Program 2 is designed to be more complex than CCM Program 1. One of the two major changes is the addition of a third resistor-capacitor pair to its RCN structure (shown in Figure 4). Based on a recommendation the literature [17], this RCN topology is more optimal as it has two resistor-capacitor pairs which model the building envelope rather than just one.

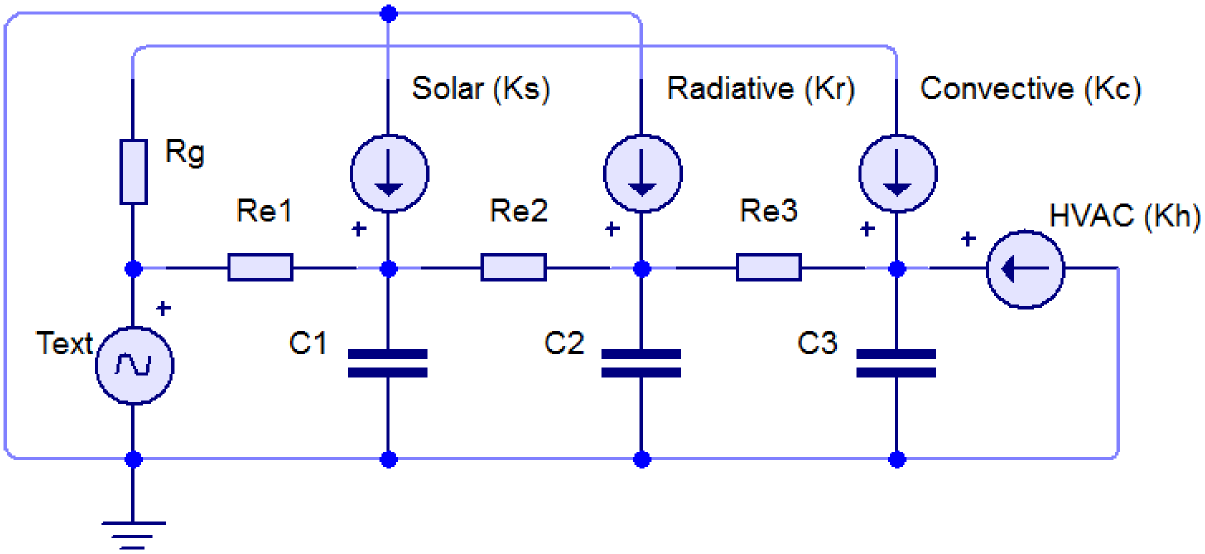


Figure 4

The other major change made to produce "RCN2" is the addition of a ground model (Rg), which links the average external air temperature to the internal air temperature.

Ground temperature is a significant factor in the thermo-dynamics of buildings. It is generally more stable than external air temperature, and so has the potential to warm the internal air space in winter and cool the internal air space in summer. The inclusion of this ground model is the result of collaborating with another student as part of a larger group project.

The state-space system matrices of RCN2 are provided below.

- $A = \begin{bmatrix} \frac{-(Re1+Re2)}{Re1*Re2*C1} & \frac{1}{Re2*C1} & 0 \\ \frac{1}{Re2*C2} & \frac{-(Re2+Re3)}{Re2*Re3*C2} & \frac{1}{Re3*C2} \\ 0 & \frac{1}{Re3*C3} & \frac{-(Re3+Reg)}{Re3*Reg*C3} \end{bmatrix};$

- $C = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix};$

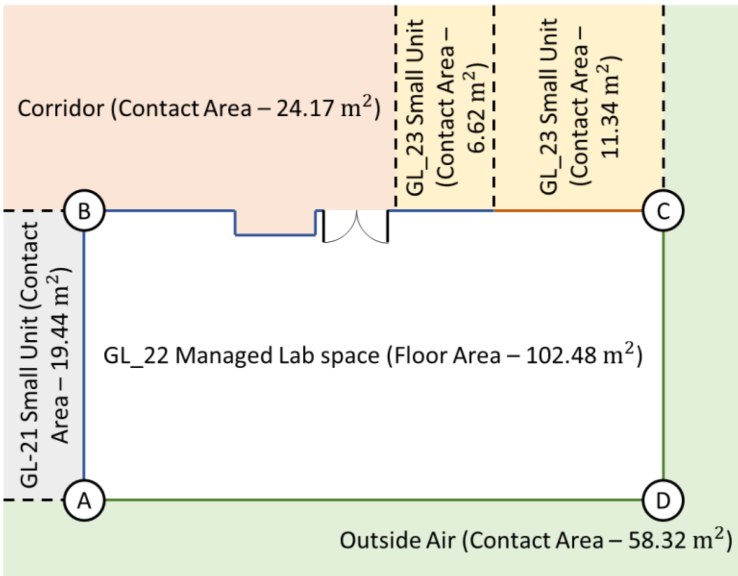
- $B = \begin{bmatrix} \frac{1}{Re1*C1} & \frac{Ks}{C1} & 0 & 0 & 0 \\ 0 & 0 & \frac{Kr}{C2} & 0 & 0 \\ \frac{1}{Reg*C3} & 0 & 0 & \frac{Kc}{C3} & \frac{Kh}{C3} \end{bmatrix}$;
- $D = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$;

Again, for clarity the time dependent vectors $\vec{x}$, $\dot{\vec{x}}$ and $\vec{u}$ are also provided.

$$\vec{x} = \begin{bmatrix} T_{C1} \\ T_{C2} \\ T_{C3} \end{bmatrix};\ \dot{\vec{x}} = \begin{bmatrix} \dot{T}_{C1} \\ \dot{T}_{C2} \\ \dot{T}_{C3} \end{bmatrix};\ \vec{u} = \begin{bmatrix} T_{ext} \\ q_{Ks} \\ q_{Kr} \\ q_{Kc} \\ q_{Kh} \end{bmatrix};$$

3.6.2. Test building-structure/ estimation and input data.

The main source of estimation and input data for the main analytical investigation is “Exeter Science Park” [35], who donated building data to the project. After multiple site visits the group working on the larger project (of which this individual report is a part) decided to request data monitoring data for Managed Lab space “GL_22” (shown in Figure 5). This room was chosen because had most thermal complexity of the rooms with full data.



Surface	Length (m)
A-B, C-D	7.2
B-C, D-A	14.4

Surface	Construction
(blue)	2*12.5mm “SoundBloc” each side of 70as50 “AcouStuds”
(orange)	250mm Concrete Shear Wall Plastered Both Sides
(green)	Mix of: 2*12.5mm “SoundBloc” each side of 70as50 “AcouStuds”, and Single glazed partition with aluminium frame
Ceiling	Unknown
Floor	Unknown

Figure 5. Note that GL_22 also contacts FL_01, FL_02 and FL_13 on the first floor. The contact areas are 11.88m^2, 31.92m^2 and 58.68m^2 respectively.

As Figure 5 shows, GL_22 only has one thermal zone. However, it is surrounded by multiple other thermal zones and outside air, making it a modelling challenge. Nevertheless, the fact that GL_22 only has one thermal zone does reduce the quantity of estimation and input data, as shown in Table 4.

Time (s)	Outside Air Temperature (°C)	BNI (J/m2)	GHI (J/m2)	G4 Room Temperature (°C)	G5 Room Temperature (°C)	G5 Room CO2 (ppm)	G6 Room Temperature (°C)	F9 Room Temperature (°C)	F10 Room Temperature (°C)	F11 Room Temperature (°C)	Boiler Flow Temperature (°C)	Boiler Return Temperature (°C)
11:15:00	19.05	6177	57306	22.67	23.8	1155	22.89	23.52	23.45	21.02	62.92	58.35
11:20:00	19.11	7027	60128	22.683	23.76	1145	22.957	23.517	23.54	21.14	62.403	58.11
11:25:00	19.17	7872	62951	22.697	23.72	1136	23.023	23.513	23.63	21.26	61.887	57.87

Table 4

In Table 4, the Science Park data is presented in its raw form; in order to be used for CCM it requires additional processing. In its raw format the estimation data is the internal air temperature time series measurements of the thermal zone of interest; this must only be checked for consistency. The input data comprises temperature and CO2 concentration time series for each room and also the flow temperatures of the boiler (input and output).

Regrettably, the data from the Science Park lacks direct and diffuse solar irradiance. These values are necessary for CCM, so they were obtained using the “CAMS Radiation Service” [36]. This European Commission website uses meteorological data to estimate irradiation at any point on the earth’s surface for a given location and time period. Again, working in collaboration with other students, the Science Park data was used to calculate the necessary model inputs: solar gains, radiative heating gains, convective heating gains and HVAC heating gains.

3.6.3. Data refinement.

The Science Park data contains many glitches e.g. timesteps which indicated that there were gaps in the data, or points where the data jumped backwards in time. A MATLAB script was written to address these glitches and ensure the number of timesteps agreed with the period of the data. If a correction left missing data, the gaps were filled using either “linear” interpolation for the date values or “p-chip” interpolation for the estimation and input quantities respectively. Figure 6 shows the MATLAB code structure used to refine the data used in this report.

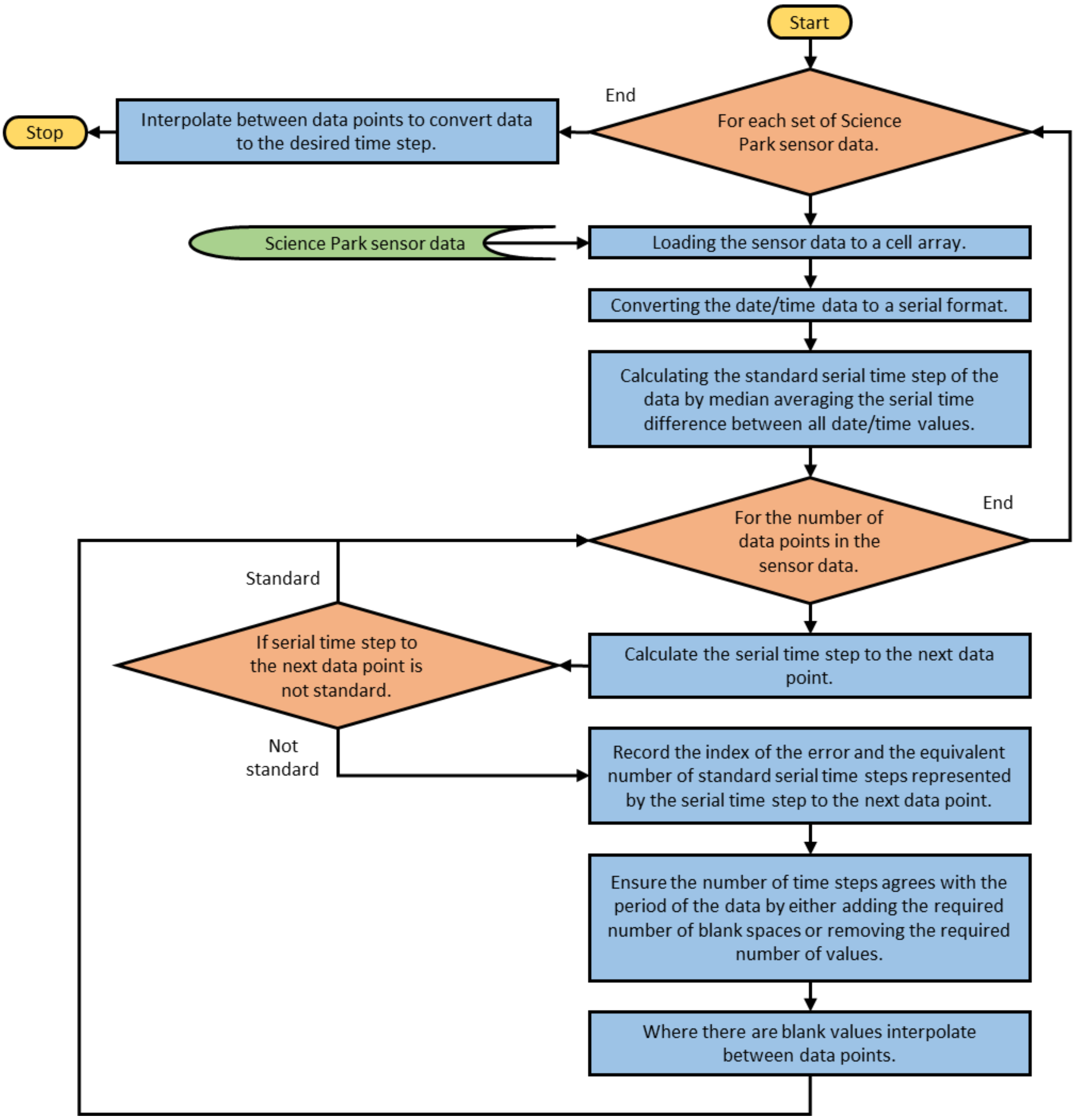


Figure 6

3.6.4. Initial RCN parameter estimation.

Again, using analytic methods, in this case with the structural information provided in Figure 5 and researched material properties, the RCN parameters for GL_22 were estimated.

- $\mathrm{Re1} + \mathrm{Re2} + \mathrm{Re3} \sim 2.237 \times 10^{-4}$ [K/W]
- $\mathrm{C1} + \mathrm{C2} \sim 4.995 \times 10^{7}$ [J/K]
- $\mathrm{C3} \sim 3.424 \times 10^{5}$ [J/K]

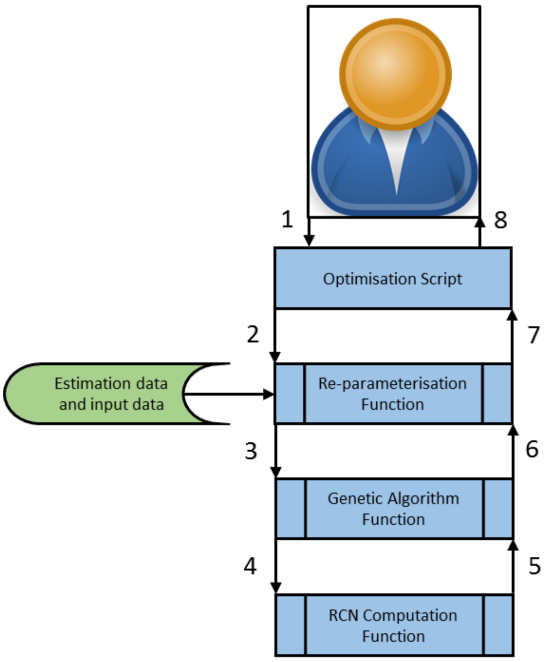
Some confidence in the calculations can be taken from the fact that the capacitor values are smaller, and the resistor values are bigger (as one would expect from a smaller structure).

3.6.1. HVAC details.

Conveniently, the HVAC layout of the LBuilding-G000 (Figure 3) and HVAC layout of the Science Park are similar enough that they are equivalent in most key aspects.

3.7. Code structure.

Figure 7 shows the MATLAB code structure used to achieve the results of this report.



Number	Data transferred
1	• Number of operations and type of operations
2	• Number of re-parameteristations • Type of RCN • Estimation/input data file name
3	• The number of initial random simulations • The 'system data' from any previous parameterisation periods • Input data for the parameterisation period
4	• Set of RCN parameters
5	• Fit • System data
6	• Best fit • Best system data • Best RCN parameters
7	• Total best fit • Total best system data • Total best RCN parameters
8	• Desired results

Figure 7

Note.

This section describes two CCM programs. Both programs use MATLAB's GA function to optimise their parameters; however, they are based on distinct RCN structures. Although each CCM program is introduced with a separate test building-structure, they can and will be used interchangeably during the analytical investigation. Also, the most direct way of demonstrating the CCM program(s) described in the theoretical background satisfy the objective "[to] adapt to suit multiple dissimilar modelling problems", is to achieve the subsequent objectives; no specific attempt will be made to prove they satisfy this objective.

4. Analytical investigation.

To achieve the first three objectives, twelve thermal models were made of LBuilding-G000 as a basis for comparison. These thermal models consisted of all the possible permutations of two weather locations, two CCM Programs and three re-parameterisation schedules (none, seasonal, monthly). For each thermal model two metrics were evaluated, the fit accuracy value and the “CPU time” taken by the CCM Program to optimise itself for the given estimation and input data.

4.1. Re-parameterisation optimisation for a virtual case.

In the theoretical background, it was hypothesised that increasing the number of re-parameterisations would result in better accuracy at the expense of simulation time. Figure 8 shows the results of modelling LBuilding-G000 with variable parameterisation schedules but with a fixed CCM Program (Program 1) and fixed weather (London).

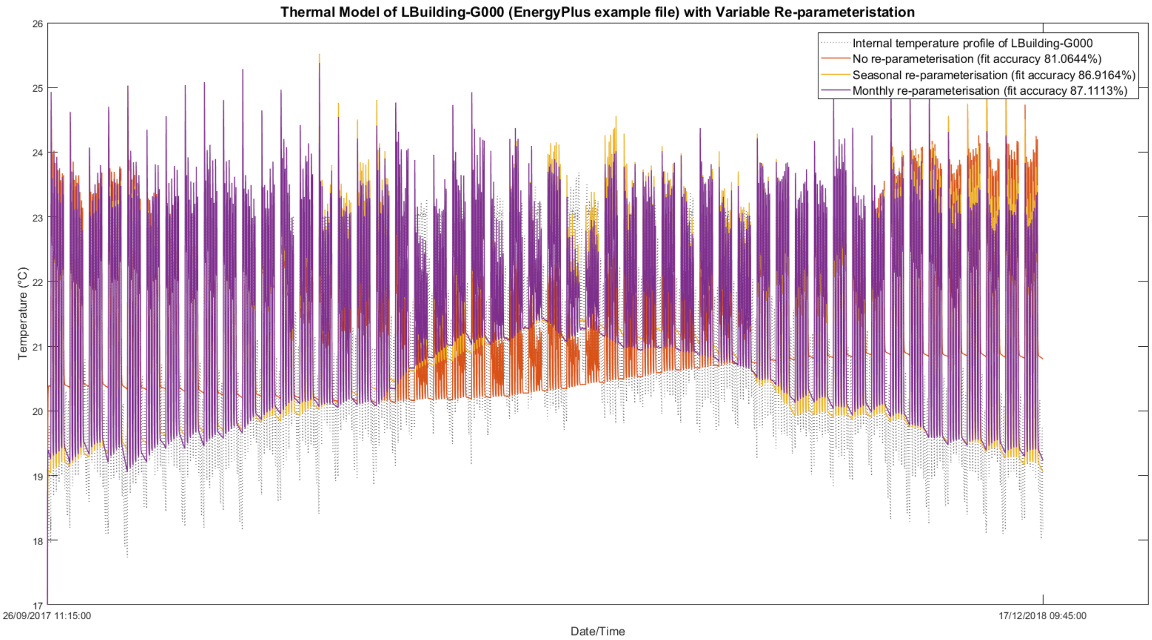


Figure 8

In Figure 8, the fit accuracy values are acceptable, however none of the re-parameterisation variations capture the seasonal or daily variation satisfactorily. To extend this comparison to all of the thermal models, it was decided to create an optimality metric which varies between 0 and 1 (as shown in Equation 15).

$$\begin{aligned}\text{optimality} &= \beta \times (\text{normalised fit accuracy}) \\ &\quad + (1-\beta) \times (1 - \text{normalised simulation time})\end{aligned} \qquad \textbf{Equation 15}$$

This optimality metric evaluates a model (or models) by weighting other normalised metrics (which also vary between 0 and 1), and it allows the level of precedence of each variable to be precisely controlled. In this case, the variable β was set to 0.5, giving equal precedence. Table 5 compares the optimality of all models (sorted by re-parameterisation schedule).

	No re-parameterisation	**Seasonal re-parameterisation**	**Monthly re-parameterisation**
average fit accuracy (%)	78.602	83.322	84.303
average simulation time (s)	944.19	499.52	517.46
optimality	0	0.91396	0.97983

Table 5

On one hand, Table 5 confirms half of the hypothesis, as increasing the number of re-parameterisations resulted in a better average fit accuracy value. On the other hand, it contradicts the other half of the hypothesis as the average simulation time tends to decrease with the number of re-parameterisations. Consequently, the optimality metric suggests monthly re-parameterisations are most optimal.

4.2. RCN optimisation for a virtual case.

Furthermore, the theoretical background hypothesises that CCM Program 2 has superior accuracy to CCM Program 1 because it has more features, but as a result it requires more simulation time. Figure 9 shows the results of modelling LBuilding-G000 with variable CCM Program (Program 1) but with a fixed re-parameterisation schedule (none) and fixed weather (London).

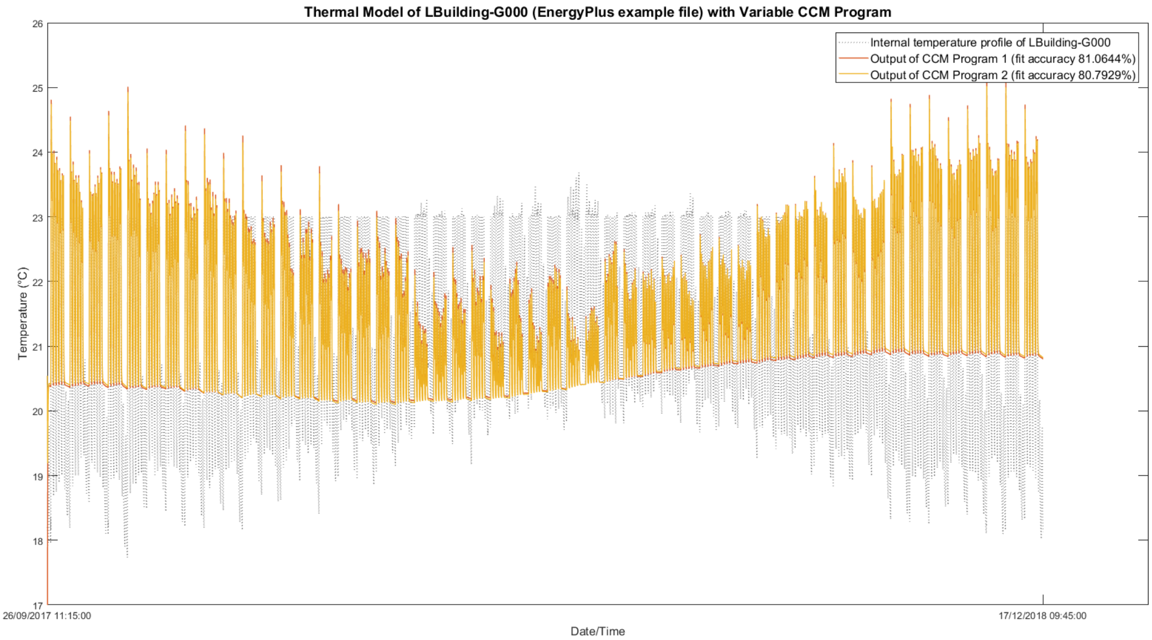


Figure 9

Because there is no re-parameterisation, the fit accuracy values of the models in Figure 9 are the lowest of any based on LBuilding-G000. Defining an optimality metric is not possible, because there are only two CCM Programs. Nonetheless, Table 6 compares the two CCM Programs across all thermal models.

	CCM Program 1	**CCM Program 2**
average fit accuracy (%)	81.993	82.160
average simulation time (s)	647.33	660.12

Table 6

Contrary to the hypothesis regarding the two CCM Programs, Table 6 shows that both are approximately equal in terms of fit accuracy and simulation time.

4.3. Verification of optimisations for a more general case.

To validate these optimisations, it was necessary to create a set of generalised data. Due to time constraints, this had to be achieved using the twelve thermal models based on LBuilding-G000 (as compiling information for a new virtual structure is too time intensive). Therefore, a modified set of estimation and input data was generated by running EnergyPlus with different weather file (equivalent to relocating the building). Figure 10 shows the effect of changing estimation data and input data had on thermal models with re-parameterisation. Note that Figures 10 and 11 have no x-axis values because the two weather files generated estimation data of differing lengths, and so the dates do not match up precisely.

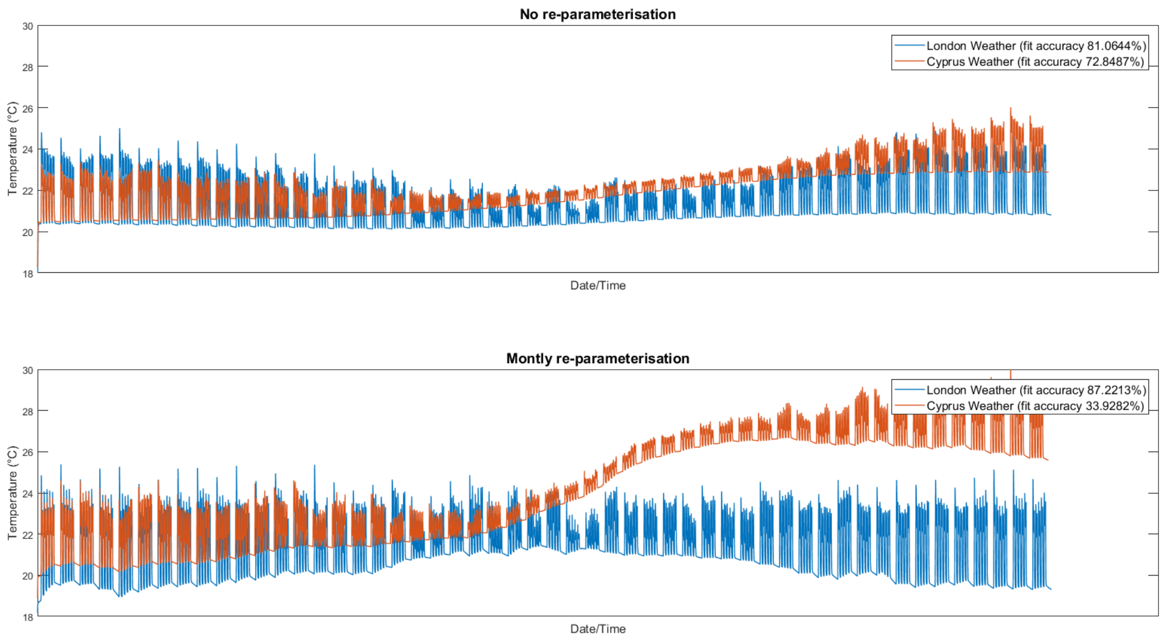


Figure 10

Figure 10 demonstrates that models with re-parameterisation are more sensitive to change; which is undesirable, as a later objective is to investigate the possibility of modelling structural alterations. Theoretically, a perfect CCM Program would create model parameters which represent the true building properties and would handle changes. It is clear that re-parameterisation tends to interrupt the identification of true building parameters.

Additionally, Figure 11 shows the effect that changing the estimation and input data had on both CCM Programs.

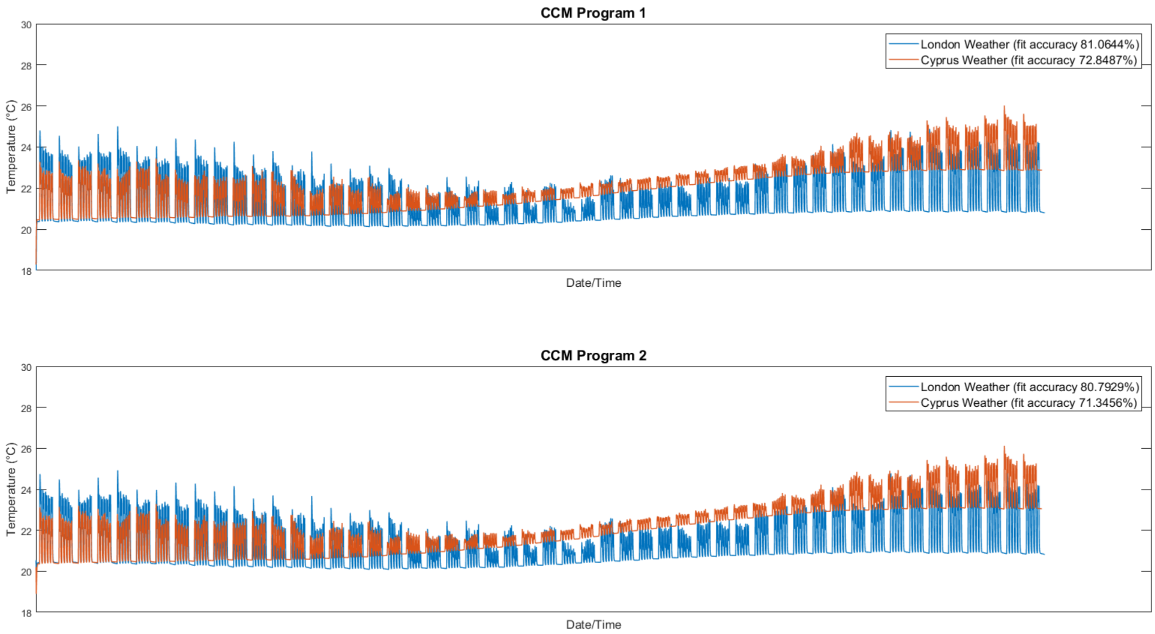


Figure 11

Once again, both CCM Models appear roughly equivalent.

4.4. Application of an optimised CCM Program in a real case.

The CCM Program used to model the real case (GL_22) was based on CCM Program 1. This was because:

- Another student had contributed to its development (e.g. the ground model).
- Based on the results from the virtual case, it did not appear to matter.

Also, based on the virtual case results, re-parameterisation was not included the CCM Program. The last two objectives require that the model parameters are as representative of reality as possible and the best way of achieving this is to avoid re-parameterisation.

Since HVAC heating gains could not be directly calculated from the Science Park input data, the temperature differential of the boiler was used to estimate the total HVAC heating power. The relationship between the boiler's temperature differential and its heating power is given in Equation 16.

$$h_s = (c_p \times \rho \times q) \times \delta T$$ **Equation 16**

Where, h_s – sensible heat, c_p – specific heat capacity, ρ – density, q – volumetric flow rate and δT – temperature differential.

The Science Park Data does not include volumetric flow rate, nor does it provide information on the distribution of the boilers energy to each room. So, it was decided to approximate this relationship with a proportionality constant as shown below.

- $h_s = k \times \delta T$

The value of this constant k was determined by the GA; as k replaces Kh in the system matrices, a new initial parameter estimate was required, which was made by dividing the average HVAC gain value of LBuilding-G000 by the average temperature differential of the Science Park's boiler. Figure 12 shows the results of using the CCM to create a Thermal Model of GL 22 for the whole period of the Science Park data.

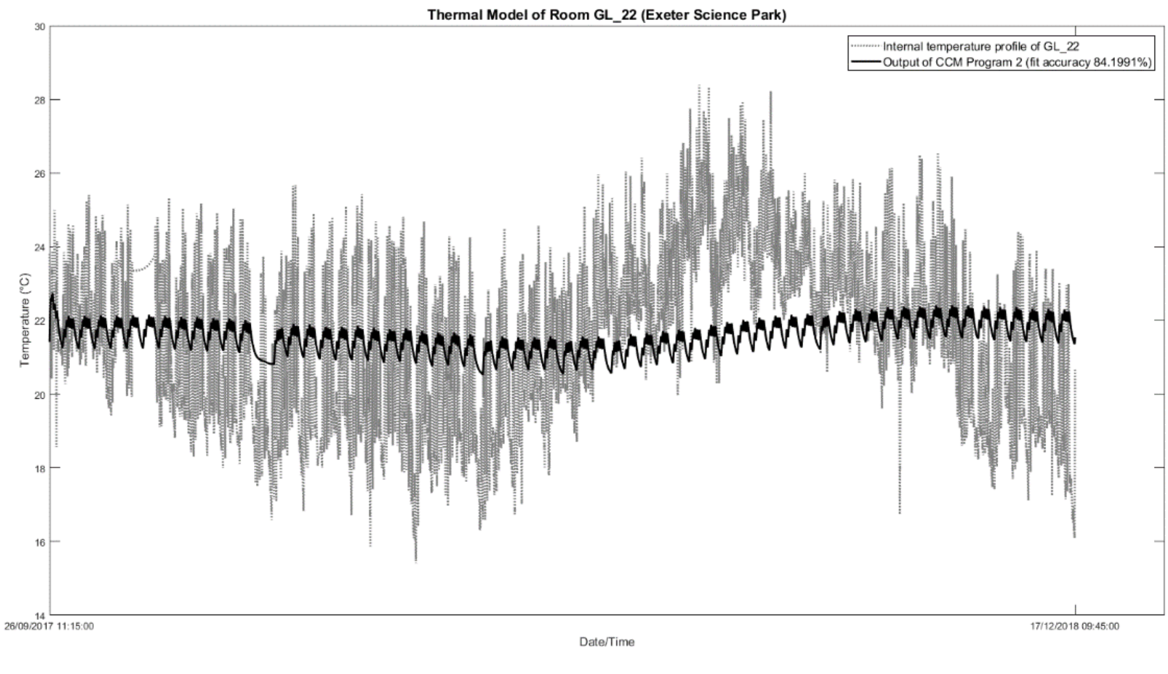


Figure 12

The optimal RCN parameters for the model are also provided in Table 7.

Re1	C1	Re2	C2	Re3	C3	Reg	Ks	Kr	Kc	Kh	T0_1	T0_2	T0_3
3.355E-04	1.340E+07	1.119E-06	1.647E+07	2.034E-04	2.071E+05	2.100E-01	5.000E-01	1.000E+00	1.500E+00	1.997E+04	1.467E+01	2.598E+01	2.158E+01

Table 7

Comparing the fit shown in Figure 12 to those based on LBuilding-G000 (Figures 8-11) it is clear that CCM Program 2 is better able to model GL_22 than LBuilding-G000. The fit accuracy value of 84.3244% is roughly 4% better than the equivalent thermal model based on LBuilding-G000. However, daily fluctuation is captured less well. This was confirmed by Figure 13, which shows examples of CCM Program 2 being used for individual days.

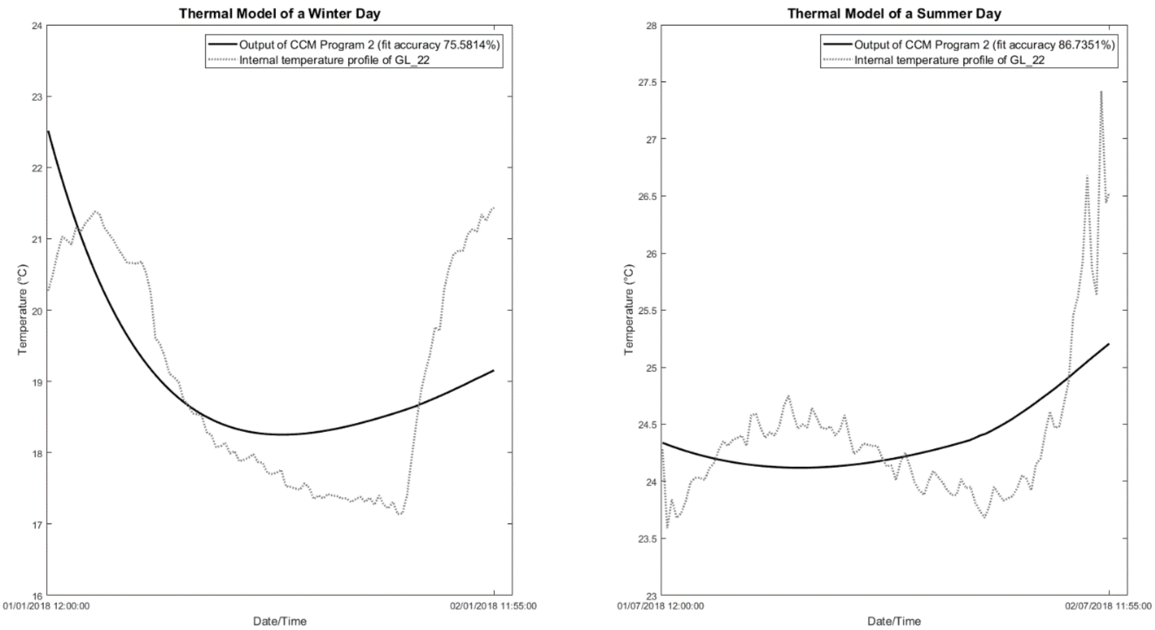


Figure 13

4.5. Calculation of building performance changes due to structural alterations.

In this section, the performance change due to a theoretical new type of window film will be investigated. Supposing that the new window film increases the thermal resistance of the building envelope by 10%, this augmentation was implemented as follows.

- $\mathrm{Re1_{new}} = 1.1 \times \mathrm{Re1_{old}};\ \mathrm{Re2_{new}} = 1.1 \times \mathrm{Re2_{old}};\ \mathrm{Re3_{new}} = 1.1 \times \mathrm{Re3_{old}}$

These changes resulted in the adjusted RCN parameter set as shown in Table 6.

Re1	C1	**Re2**	C2	**Re3**	C3	Reg	Ks	Kr	Kc	Kh	T0_1	T0_2	T0_3
3.691E-04	1.340E+07	**1.230E-06**	1.647E+07	**2.238E-04**	2.071E+05	2.100E-01	5.000E-01	1.000E+00	1.500E+00	1.997E+04	1.467E+01	2.598E+01	2.158E+01

Table 6

Figure 14 shows the result of re-simulating the thermal model of GL 22 with the adjusted RCN parameter set.

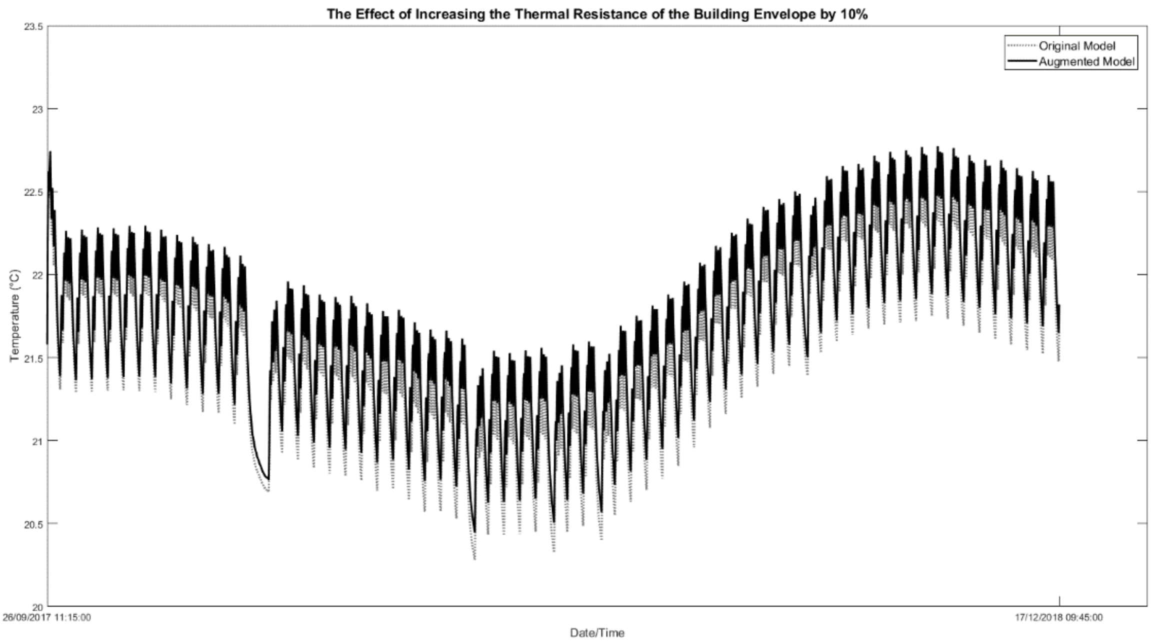


Figure 14

The results in Figure 14 are exactly what one would expect if the thermal resistance of the building envelope was increased. There is no temperature control built into the CCM Program, so the heat retained by the more resistant building envelope is shown by a ~0.1°C increase in temperature, which is gained in the first days and maintained throughout whole period.

4.6. Calculation of heating/cooling energy requirements.

Of course, designers are generally more concerned with saving energy than increasing temperature. Furthermore, the temperature of GL 22 is monitored and controlled by a building management system, and therefore assumed to be optimal. It would be more useful (than calculating a temperature increase) to calculate the energy saving compared to the original RCN parameter set, assuming the temperature was controlled so it matched the original temperature profile.

The B matrix is non-square and so it is not possible to re-calculate the input time-series ($\vec{u}$) using matrix algebra. The closest re-arrangement of the state-space system is as follows.

- $\mathrm{B} \times \vec{\mathrm{u}} = \dot{\vec{\mathrm{x}}} - \mathrm{A} \times \underline{\mathrm{x}}$