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Article

A Multi-Objective Design Optimization of a New Build Future Home Standard House in Controlled Conditions

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Abstract: This paper aims to determine the optimal construction strategies for new build houses in the UK to minimise heating energy demand and discomfort hours. The research utilises a previously calibrated model of "The Future Home" in Energy House 2.0's environmental chamber. Eight design variables were optimised including multiple building fabric specifications, air permeability rates, and heating setpoint temperatures. Three optimisation scenarios were investigated: fixed heating setpoints, variable heating setpoints, and variable setpoints with comfort constraints. The analysis revealed that while fixed heating setpoints showed limited optimization potential, variable setpoint scenarios identified three distinct clusters of optimal solutions. The optimization consistently favored superior building fabric parameters, though air permeability solutions became more nuanced with variable heating control. When constrained to maximum 400 discomfort hours, solutions required elevated heating setpoints (22-23 °C) while maintaining high fabric specifications. These findings advance building optimization methodology by demonstrating the importance of heating control flexibility and comfort constraints in achieving optimal performance, while the use of a calibrated model in controlled conditions overcomes the limitations of previous studies that relied on uncalibrated or hypothetical models.

Keywords: multi-objective optimization; dynamic thermal simulation; thermal comfort; controlled conditions; future home standard

1. Introduction

The residential building sector is a significant contributor to the UK's carbon emissions, driving the development of increasingly stringent building standards and regulations. While the PassivHaus standard has long been recognised as a gold standard for energy-efficient building design, its widespread adoption has been limited by cost implications [1]. The UK government has proposed the Future Homes Standard (FHS) through consultation documents [2], with planned implementation in 2025, aiming to establish more practical yet effective requirements for low-carbon residential buildings. These standards primarily govern building fabric performance through specifications for U-values of external walls, roofs, ground floors, and windows, as well as air permeability rates. However, the relationship between increasing insulation levels and energy performance is not linear, with studies suggesting diminishing returns beyond certain thresholds [3–5]. While previous studies have explored building fabric optimization, their results often face uncertainties due to variable environmental conditions and occupancy patterns in real-world settings [6,7]. This research addresses these limitations by utilising Energy House 2.0, a state-of-the-art research facility featuring two environmental chambers capable of simulating extreme weather conditions from -20 °C to +40 °C, including wind, rain, snow, and solar radiation.

For instance, determining a building's Heat Transfer Coefficient (HTC) through coheating tests traditionally requires extensive measures to control environmental factors, such as using aluminium foil to eliminate solar radiation effects [8], and necessitates the building being unoccupied. In contrast, the controlled environment of Energy House 2.0 allows these tests to be completed efficiently with lower uncertainty within several days. This facility contains "The Future Home" (TFH) in

environmental chamber one, a prototype house constructed by Bellway Homes to demonstrate anticipated FHS compliance, which serves as the case study for this research [9]. Recent experimental studies have established comprehensive baseline performance data for TFH through co-heating tests, heat-flux measurements, and air permeability testing under these controlled conditions [9].

Using TFH as a case study, these precisely measured parameters enable the development of a calibrated Dynamic Thermal Simulation (DTS) model using DesignBuilder [10]. The resulting multi-objective optimization study within the controlled environment of Energy House 2.0 therefore offers unprecedented reliability, as it reduces the uncertainties typically associated with real-world conditions. This unique setup provides an opportunity to conduct reliable optimization studies that can directly inform industry practices, particularly as UK housebuilders target the construction of 300,000 homes annually under the forthcoming FHS requirements [2]. This approach represents a significant advancement in building performance optimization methodology, bridging the gap between theoretical models and practical applications.

2. Literature Review

2.1. Multi-Objective Optimization for Building Performance Simulation

Multi-objective optimization (MOO) has gained significant attention in building performance simulation due to its ability to handle complex, often conflicting objectives. In design optimization, researchers have successfully applied MOO to optimize building envelope parameters, Heating Ventilation and Air-Conditioning (HVAC) systems, and renewable energy integration. For instance, Nguyen et al. demonstrated the application of MOO in optimizing window-to-wall ratio and insulation thickness to balance energy consumption and thermal comfort [11]. Similarly, Ascione et al. employed MOO for cost optimal retrofitting strategies, considering both energy savings and investment costs [12]. Asadi et al. investigated various retrofit measures including insulation materials, window types, and HVAC systems to minimize energy consumption, retrofit cost, and thermal discomfort hours [13]. Wang et al. implemented MOO to optimize building retrofitting measures and their quantities to maximise energy savings and economic benefits while minimising payback period and life cycle costs [14]. Similarly, Asadi et al. applied a multi-objective optimization model towards minimising energy consumption and investment costs by optimizing window types, insulation materials, and solar collector configurations in residential buildings [15]. Delgarm et al. optimized building energy performance and thermal comfort, considering variables such as room rotation, window size, setpoint temperatures, and envelope properties in different climate regions of Iran [16]. More recently, Rosso et al. developed a comprehensive framework to optimize building retrofit in Mediterranean climate, examining eleven different variables including envelope systems, solar technologies and shading strategies to simultaneously minimise investment cost, energy cost, energy consumption and carbon dioxide emissions [17]. D'Agostino et al. utilised MOO to optimize building envelope, HVAC system configurations and renewable energy sources to minimise cooling demand, heating demand and investment costs while ensuring Nearly Zero Energy Buildings (NZEB) guidance [18]. Finally, Benincá et al. employed MOO to optimize solar orientation of two residential building shapes ("H" and linear) to simultaneously minimise cooling and heating demands in Southern Brazil [19].

2.2. Multi-Objective Optimization Algorithms

The most widely adopted approach is the Non-dominated Sorting Genetic Algorithm II (NSGA-II), developed by Deb et al. [20], which offers a balance between solution convergence and distribution. This algorithm is implemented in commercial software like DesignBuilder, providing a fast and elitist multi-objective optimization method.

As Jankovic explains, NSGA-II operates through genetic operations of crossover, mutation, and reproduction [7]. The algorithm combines building performance parameters into chromosomes and manipulates these using genetic operations. Starting with random population initialization, the

solution space is "peppered" with the starting chromosomes. Through successive generations, chromosomes are paired and split at random positions (crossover), occasionally mutated to explore new parts of the solution space, and selected based on fitness criteria (reproduction).

The efficiency of NSGA-II is demonstrated in Jankovic's study, where it reduced the search space from 920,000 potential cases to 737 cases while maintaining high accuracy in building performance prediction. While DesignBuilder notes a limitation in NSGA-II's constraint handling capability [21], the algorithm's proven effectiveness in ranking competing objectives makes it valuable for building optimization problems.

3. Materials and Methods

3.1. Energy House 2.0 and TFH Experimental Study

The experimental study evaluated the fabric performance of TFH and identified performance gaps between the design intent and actual measured results [9] (Figure 1). These gaps, representing differences between design models, based on the Standard Assessment Procedure (SAP) and real-world performance, were assessed using measurements of the HTC [22–24], U-values [25], and airtightness [26].

The overall fabric heat loss of TFH was 7.7% higher than predicted, increasing the Dwelling Fabric Energy Efficiency (DFEE) by 3.54 kWh/m²/year. The main issue was an airtightness value of 4 m³/h·m², 61% worse than the design target of 2.5 m³/h·m², caused by additional sockets, service penetrations, and insulation gaps at key junctions. Thermal imaging confirmed these issues.

The roof underperformed by 56% due to poorly installed insulation and a large loft decking area that hindered inspection. By contrast, the external walls performed well, with the rendered wall meeting design expectations thanks to continuous PIR insulation that minimised thermal bridging.

A metric called "Point Thermal Transmittance" (PTT) was developed [9] to account for the numerous variables influencing the U-value of ground floors, including thermal bridging, air brick impact, perimeter effect, and insulation geometry. This accounts for the limitations of comparing average heat flux plates measurements to design U-values. As stated in the report, the PTT calculation method mirrors the formula, presenting a range of PTTs (U-values) rather than the average [9]. Ground floor PTT-value were broadly consistent with the design, though challenges in measuring suspended floors highlighted a need for standardised methods.

Windows and doors performed as expected, though limited manufacturer data constrained the analysis. Centre-pane measurements aligned with specifications, while the front door overperformed by 29%, likely due to simplified U-value calculations.



Figure 1. Front elevation of TFH in Energy House 2.0 Environmental Chamber one (left) and TFH modelled in DesignBuilder (right).

3.2. TFH and Building Standards Context

The optimization study utilises TFH as its case study. Table 1 presents the building's thermal performance specifications alongside relevant UK standards for context. The values listed under UK Building Regulations represent the maximum permitted values for new dwellings [27]. PassivHaus standards represent a more stringent voluntary standard, it specified a maximum U-value of 0.15 W/m²K for all opaque building envelope components (external walls, loft ceiling and ground floor) [28]. The design values of TFH demonstrate compliance with the UK FHS requirements. For comprehensive details of the experimental testing methodology and results, readers are referred to Fitton et al. [9]. The development and calibration process of the DTS model used in this study is fully documented in Tsang et al. [10].

Table 1. Thermal performance parameters comparison between TFH design specifications, as-built measurements, and relevant UK and international building standards.

Building fabric element	Design	As-built	UK FHS	UK Building regulations	PassivHaus standard
External wall U-value (W/m ² K)	0.18	0.17	0.18	0.26	0.15
Loft ceiling U-value (W/m ² K)	0.09	0.14	0.11	0.16	0.15
Ground floor PTT-value (W/m ² K)	0.11	0.14	0.13	0.18	0.15
Windows U-value (W/m ² K)	1.20	-	1.20	1.60	0.80
French Door U-value (W/m ² K)	1.40	-	1.20	-	-
External Door U-value (W/m ² K)	1.00	-	1.00	1.60	0.80
Air infiltration rate @50 Pa (m ³ /hm ²)	2.50	4.00	5.00	8.00	0.60

3.3. Selection of Variables for Multi-Objective Optimization

Eight building parameters were selected for multi-objective optimization to minimise heating energy consumption and thermal discomfort in TFH (Table 2). These parameters were chosen based on three criteria: significant discrepancies between design and as-built values, potential for practical improvements through retrofit measures, and varying recommendations across different standards. The parameters include envelope U-values (walls, loft, windows, French doors), air permeability, and heating setpoints for living and other zones. Each parameter underwent multiple iterations to evaluate its performance impact. The following sections detail the selection rationale and range for each variable.

Table 2. Summary of design variables perturbations used in multi-objective optimization.

Variable	Baseline	Perturbations	Iterations
External wall U-value (W/m ² K)	0.17	0.12, 0.13, 0.14, 0.15, 0.16, 0.17 , 0.18, 0.19, 0.20	9
Loft ceiling U-value (W/m ² K)	0.14	0.09, 0.10, 0.11, 0.12, 0.13, 0.14 , 0.15, 0.16	8
Window U-values (W/m ² K)	1.2	0.8, 0.9, 1.0, 1.1, 1.2 , 1.3, 1.4, 1.5, 1.6	9
French door U-value (W/m ² K)	1.4	1.0, 1.1, 1.2, 1.3, 1.4 , 1.5, 1.6, 1.7, 1.8	9
Air permeability rate @50 Pa (m ³ /hm ²)	4.0	2.5, 3.0, 3.5, 4.0 , 4.5, 5.0	6
Ground floor PTT-value (W/m ² K)	0.14	0.11, 0.12, 0.13, 0.14 , 0.15, 0.16, 0.17, 0.18	8
Living room heating set-point (°C)	21	19, 20, 21 , 22	4
Other zone heating set-point (°C)	18	18 , 19, 20, 21	4

3.3.1. External Walls

External wall U-value was selected as a design variable due to its significant impact on thermal performance and retrofit potential, specifically through the existing 63 mm ventilated cavity which

offers an opportunity for additional insulation. The current wall assembly consists of brickwork, the 63 mm ventilated cavity, OSB board, insulated timber frame, PIR insulation board, service void, and plasterboard, achieving an as-built U-value of 0.17 W/m²K [9].

The optimization range (0.12-0.20 W/m²K) explores various cavity insulation scenarios by filling this existing 63 mm void. The lower bound (0.12 W/m²K) represents increased levels of thermal insulation, while intermediate values correspond to commercial options, such as high-performance glass wool (0.14 W/m²K), Knauf Supafil CarbonPlus (0.15 W/m²K) [9], and enhanced mineral wool (0.16 W/m²K). The upper range (0.19-0.20 W/m²K) accounts for potential non-uniform insulation distribution. Values above 0.20 W/m²K were excluded despite the UK building regulation limit of 0.26 W/m²K, as they are improbable with the existing construction.

3.3.2. Loft Ceiling

Loft ceiling U-value was selected as a design variable due to significant deviation between design (0.09 W/m²K) and as-built performance (0.14 W/m²K), primarily caused by disturbed and non-uniform insulation distribution, inconsistent thickness throughout the loft space, and potential air infiltration issues identified through thermographic imaging [9]. The optimization potential is particularly relevant as approximately 50% of the loft area is decked, limiting intervention options.

The optimization range (0.09-0.16 W/m²K) explores various remediation scenarios. The lower bound (0.09 W/m²K) represents the original design specification, achievable through comprehensive remediation of installation issues. Intermediate values (0.10-0.13 W/m²K) correspond to incremental improvements through insulation redistribution, thermal bridging reduction, and air sealing measures. The upper range extends to 0.16 W/m²K, aligning with UK building regulations, while accounting for scenarios with reduced insulation thickness from design specification. This range reflects both practical constraints of the decked loft space and technically feasible improvements

3.3.3. Windows and French Door

Window upgrades present significant retrofit potential in TFH. The current installation features double-glazed windows with a manufacturer-specified combined U-value (frame and glazing) of 1.2 W/m²K, meeting the FHS requirements but offering potential for enhancement [9].

The optimization range (0.8-1.6 W/m²K) explores various glazing technologies. The lower bound (0.8 W/m²K) aligns with PassivHaus standards and represents enhanced triple glazing with low-emissivity coatings and inert gas filling. Intermediate U-values of 1.0 W/m²K represents standard triple glazing according to UK SAP calculations [29]. The upper range extends to 1.6 W/m²K, aligning with current UK building regulations, to account for potential performance variations. Similarly, French doors follow a complementary optimization range (1.0-1.8 W/m²K), with the current installation having a manufacturer-specified combined U-value of 1.4 W/m²K. This coordinated approach enables evaluation of whole-house glazing strategies while maintaining technical feasibility.

3.3.4. Air Permeability Rate

Air permeability rate shows significant scope for improvement, with current measured performance of 4.0 m³/h·m² at 50 Pa deviating from the design value of 2.5 m³/h·m². This difference is primarily attributed to additional service penetrations installed for research purposes [9].

The optimization range (2.5-5.0 m³/h·m²) explores various airtightness scenarios. While the PassivHaus standard recommends 0.6 m³/h·m², and values below 1.5 m³/h·m² are technically achievable, such low air permeability rates would require enhanced sealing techniques and potentially Mechanical Ventilation with Heat Recovery (MVHR). Therefore, the lower bound (2.5 m³/h·m²) represents the design value. The upper range extends to 5.0 m³/h·m², representing the

maximum allowable value under FHS. This range allows for analysis of various performance scenarios within practical and regulatory constraints.

3.3.5. Ground Floor

Ground floor thermal performance shows complexity in assessment, with an as-built PTT-value of 0.14 W/m²K exceeding the design value of 0.11 W/m²K. The optimization range (0.11-0.18 W/m²K) explores various performance scenarios. The lower bound (0.11 W/m²K) represents potential improvement to design stage performance, while the upper bound aligns with UK building regulations maximum allowable value. Intermediate values account for potential performance variations due to thermal bridging effects, air movement through ventilation bricks, and insulation distribution patterns.

3.3.6. Heating Setpoint Temperatures

Heating setpoint temperatures were differentiated between living room at 21 °C and other zones at 18 °C, based on varying occupancy patterns and comfort requirements. These baseline values follow DesignBuilder default guidance [21].

The optimization ranges consider multiple standards: SAP recommends 21 °C for living areas and 18 °C for other zones, PassivHaus standard specifies a consistent 20 °C [28], CIBSE suggests 20 °C for living areas and 18 °C for bedrooms [30], while ASHRAE defines comfort zones of 20-24 °C for living areas and 18-21°C for bedrooms [31]. The living room range of 19-22 °C and other zones range of 18-21°C explore this variation while maintaining zonal temperature differences. These ranges enable evaluation of energy demand and comfort trade-offs across four discrete temperature steps, with constant heating setpoints assumed throughout each zone except storage areas.

3.4. Running Multi-Objective Optimization

Multi-objective optimization was performed using the calibrated energy model from Tsang et al. to evaluate three scenarios: fixed heating setpoints, variable heating setpoints, and variable heating setpoints with a 400-hour thermal discomfort constraint. The optimization targeted two objectives: minimising heating energy demand and thermal discomfort hours, with the latter defined by exceedance of ASHRAE 55-2004 winter clothing comfort boundaries based on zone humidity ratio and operative temperature [32].

The optimization utilised DesignBuilder's default genetic algorithm settings with maximum generations of 100, convergence criteria of 5 generations, and initial population size of 20. The solution space of 8,211,456 combinations was explored until convergence was achieved, with all simulations performed on an HP ZBook (i9-13950HX processor, 64GB RAM).

4. Results and Discussion

4.1. Fixed Heating Set-Point Optimization Analysis

The results, as illustrated in Figure 2, demonstrate a distinct linear correlation between electric heating demand and winter clothing discomfort hours when the heating setpoint was fixed. The simulation achieved convergence after 37 generations with 669 iterations, yet a true Pareto front was not established, suggesting limited optimization potential under these constraints. The simulation shows only 5 optimal designs (red square).

Furthermore, the findings underscore the complexities of building performance optimization when constraining individual variables. The interdependence of building parameters suggests that fixing any single variable may significantly limit the available trade-off options for designers. Of particular concern is the potential for cross-compensation among variables, whereby the optimization algorithm may suggest building physics properties that deviate from realistic values to compensate for the constrained parameter.

Given the UK's heating-dominated climate, the analysis used a constant winter clothing insulation value throughout the annual simulation period. While this approach could result in relatively high observed discomfort hours (1750-2080 hours), previous research has demonstrated that incorporating adaptive clothing behaviours into thermal comfort simulations yields substantially improved results [8], highlighting a potential limitation in the current methodology.

Notably, the single Pareto solution suggests an optimization tendency towards maximizing building envelope performance, indicating that optimal designs favour superior external wall, loft ceiling, and window constructions, combined with minimal air permeability rates. This finding aligns with established building physics principles but may not fully capture the economic and practical constraints of real-world applications.

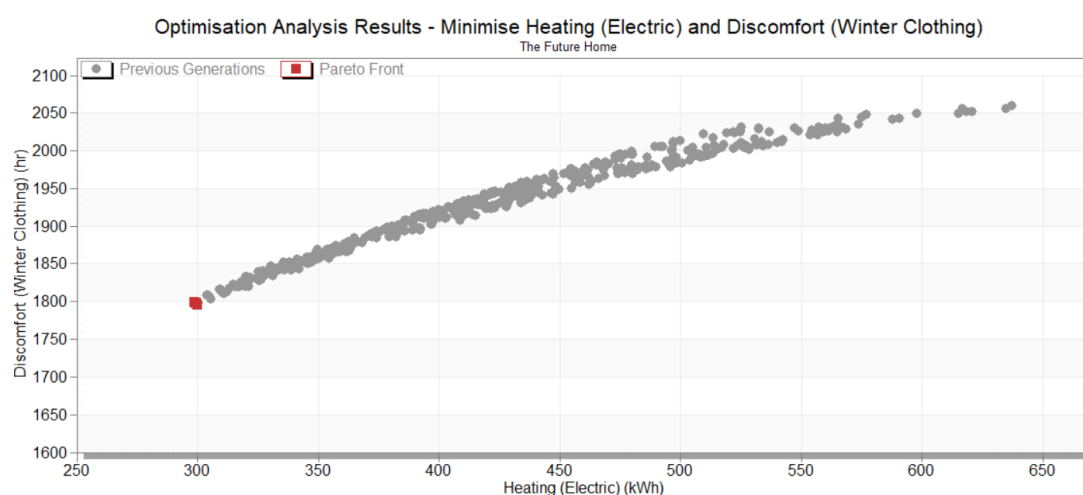


Figure 2. Optimization results of electric heating demand versus winter clothing discomfort hours. Grey dots: previous generations; red square: Pareto solution (37 generations).

4.2. Variable Heating Set-Point Optimization Analysis

The multi-objective optimization with variable heating set-points demonstrated robust convergence after 66 generations, encompassing 1,289 iterations (Figure 3). The results revealed a well-defined Pareto front, clearly illustrating the inherent trade-offs between occupant thermal discomfort and heating energy consumption. This trade-off relationship manifests in three distinct clusters of optimal solutions, suggesting multiple viable design strategies. The simulation shows 78 optimal designs (red squares).

Similarly to the fixed set-point analysis, the optimal designs consistently favoured superior external wall, loft ceiling, and window constructions, confirming these elements as crucial parameters for simultaneously minimising both discomfort hours and heating demand. However, a notable departure from the fixed set-point scenario emerged in the air permeability optimization. Rather than consistently driving towards minimum air permeability rates, the variable set-point optimization revealed more nuanced solutions, suggesting a more complex interaction between ventilation and thermal performance when heating control strategies can adapt.

These findings highlight the limitations of conventional design processes that rely on limited simulation iterations. Such restricted exploration of the solution space risks converging on sub-optimal solutions, potentially resulting in buildings that underperform throughout their lifecycle.

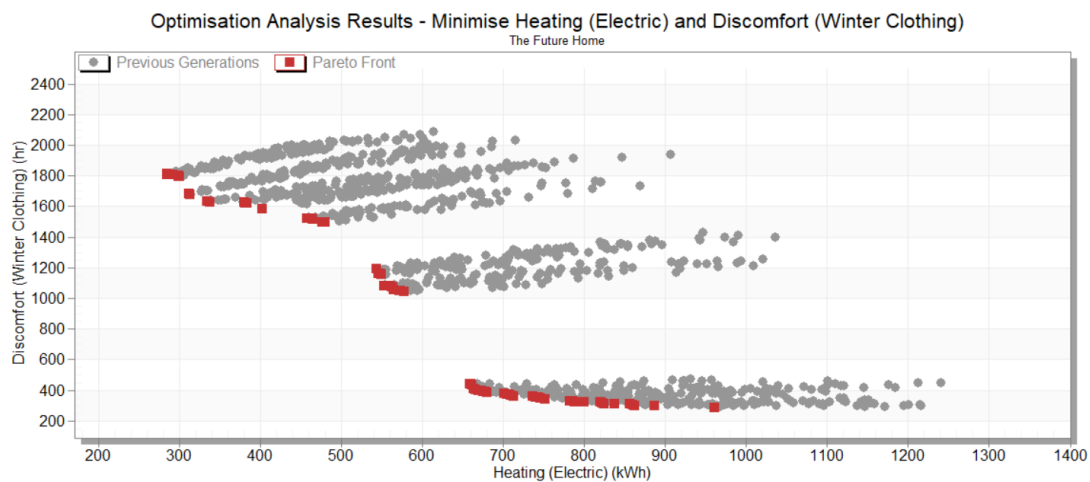


Figure 3. Optimization results of electric heating demand versus winter clothing discomfort hours, showing Pareto front evolution. Grey dots: previous generations; red squares: Pareto solutions (66 generations).

4.3. Constrained Optimization Analysis with Maximum Discomfort Threshold

The multi-objective optimization process, operating under a constraint of 400 discomfort hours, achieved robust convergence after 79 generations and 1,487 iterations. The analysis yielded a well-defined Pareto front, similar to the results shown in Figure 2. However, the increased number of generations required for convergence suggests inherent variability in the optimization process, highlighting the stochastic nature of the algorithm.

When implementing a constraint of 400 discomfort hours, the optimization results yielded a significantly reduced solution space, with only 43 optimum designs, shown as Pareto points, meeting the comfort criterion (Figure 4).

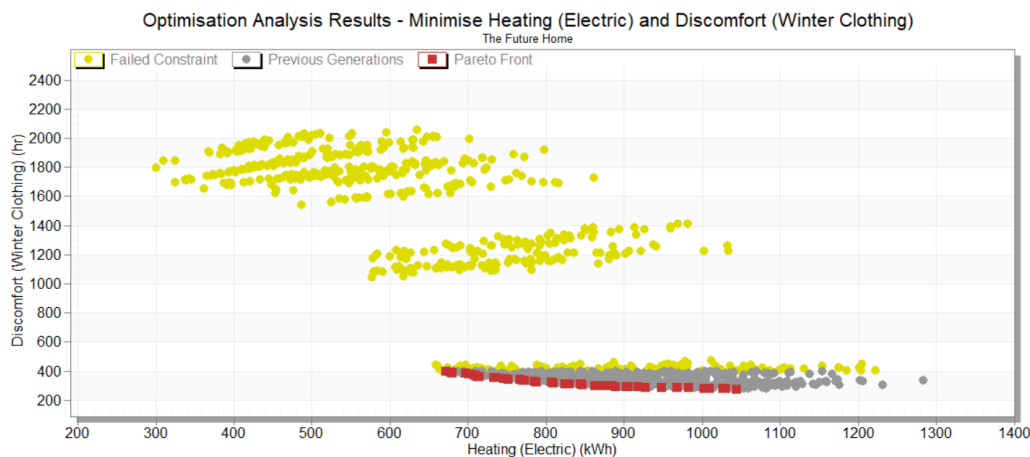


Figure 4. Optimization results of electric heating demand versus winter clothing discomfort hours, showing Pareto front evolution. Grey dots: previous generations; red squares: Pareto solutions (79 generations); yellow squares: rejected solutions due to constraint.

This constraint effectively filtered out a substantial portion of the previously viable solutions from the analysis in Figure 3. The remaining optimal solutions exhibited similar trends to the unconstrained analysis, particularly in terms of building envelope specifications. However, a distinctive characteristic emerged in the heating control strategy, with optimal solutions consistently favouring higher heating set-points of 22 °C to 23 °C. This finding emphasises that maintaining elevated heating set-points becomes crucial for achieving occupant thermal comfort requirements in the UK climate context.

The Pareto front in Figure 4 represents a design decision making tool, which generally shows that higher heating energy consumption results in lower discomfort hours and vice versa. To investigate this in more detail, a quantified summary taken from the two extremes of the Pareto front, is shown in Table 3.

Table 3. Summary of extremes of design parameters from the Pareto front.

Pareto extreme	Heating (Electric) (kWh)	Discomfort (Winter Clothing) (hr)	Air permeability rate @50 Pa (m^3/hm^2)	Glazing U-value ($\text{W}/\text{m}^2\text{K}$)	Living Room Heating set-point temperature ($^{\circ}\text{C}$)	Other Rooms Heating set-point temperature ($^{\circ}\text{C}$)
(1)	672	397	2.5	0.8	22	22
(2)	1044	276	5.0	1.6	22 (23)*	22
Difference (2)-(1)	372	-101	2.5	0.8	0 (1)*	0

*in the case of the living room there is only a single occurrence of 23 $^{\circ}\text{C}$ set-point temperature within the 43 Pareto points.

As it can be seen from this table, the increase of 372 kWh of heating energy from the lower to the upper extreme contributes to 101 discomfort hours reduction. This coincides with air permeability rates increase from 2.5 m^3/hm^2 to 5.0 m^3/hm^2 , and with the increase glazing U-value from 0.8 $\text{W}/\text{m}^2\text{K}$ to 1.6 $\text{W}/\text{m}^2\text{K}$. The heating set-point temperatures of 22 $^{\circ}\text{C}$ for the living room and the other rooms was constant throughout this range, except for a single occurrence of 23 $^{\circ}\text{C}$ as shown in Table 3. The constant set-temperatures indicate that temperature uniformity across all rooms leads to better thermal comfort. Whilst the increased glazing U-value is a counter-intuitive contributor to the decrease of thermal discomfort hours, this could be one of the causes of increased heating, which in turn leads to better thermal comfort. Similarly, the increased air-permeability rate is a counter-intuitive contributor to the increase of thermal discomfort hours, but this could also be one of the causes of increased heating that leads to better thermal comfort. It can be argued that the increased air-permeability rate also leads to the increased amount of fresh air per person and to better internal air quality, although this is not accounted for under discomfort hours. These few counter-intuitive matters will be investigated in future research in controlled laboratory conditions.

5. Conclusions

This study employed multi-objective optimization on a calibrated model of TFH in the controlled environment in Energy House 2.0 to determine optimal construction strategies for new UK homes. The optimization analysis revealed several key insights: 1) fixed heating setpoints demonstrated limited optimization potential, while the optimization consistently favoured superior building fabric across all scenarios. 2) Variable setpoint scenarios produced three distinct clusters of optimal solutions and showed more nuanced air permeability solutions compared to the fixed setpoint's drive toward minimum rates. 3) When constrained to maximum 400 discomfort hours, solutions required elevated heating setpoints of 22-23 $^{\circ}\text{C}$ while maintaining superior building fabric.

The Pareto front shown in this analysis represents a range of trade-off solutions that designers and developers can use in order to achieve different design objectives with confidence. Otherwise, design solutions will not be rigorously tested and could lead to inferior building performance. The few counter-intuitive occurrences of the results reported in the previous section will be investigated in future research.

Future research will extend this work through parallel optimization of another case study in Energy House 2.0 called "eHome2" [33], incorporating additional design variables such as building orientation, heat pump Coefficient of Performance (COP), lighting, and Photovoltaic panel sizing. Additional objectives such as carbon emissions and building costs could be evaluated, while further

constraints like summer overheating hours could be introduced to enhance the optimization framework.

Nomenclature

FHS	-	Future Homes Standard
HTC	-	Heat transfer Coefficient
DTS	-	Dynamic Thermal Simulation
MOO	-	Multi-objective optimisation
HVAC	-	Heating, ventilation and air-conditioning
NZEB	-	Net Zero Energy Building
NSGA-	-	Non-dominated Sorting Genetic Algorithm

II

TFH	-	The Future Home in Energy House Labs Environmental Chamber 1 developed in collaboration between Bellway Homes and the University of Salford
MVHR	-	Mechanical Ventilation and Heat Recovery
PTT	-	Point Thermal Transmittance
eHome2	-	Experimental house in Energy House Labs Environmental Chamber 1 developed in collaboration between Barratt Developments, Saint-Gobain, and the University of Salford.

Author Contributions: Conceptualization, C.T. and L.J.; methodology, C.T. and L.J.; validation, C.T.; investigation, C.T. and L.J.; resources, R.F.; data curation, G.H.; writing—original draft preparation, C.T. and L.J.; writing—review and editing, All; supervision, L.J. and R.F. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Models and data are available on request.

Conflicts of Interest: The authors declare no conflicts of interest.

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