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Research Paper

Comfort-aware Distributionally robust chance-constrained scheduling of PV-assisted heat pumps under dynamic tariffs: A DOE–ANOVA interaction analysis

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ABSTRACT

Purpose: This paper develops an uncertainty-aware optimisation framework for smart heat pump (HP) operation that minimises electricity cost while maintaining thermal comfort under time-varying tariffs and uncertain PV generation.

Design/methodology/approach: A Day-ahead scheduling model is formulated using distributionally robust chance-constrained programming (DR-CCP) to control the probability of comfort-constraint violation under distributional ambiguity in renewable forecast errors. Thermal comfort is represented using either (i) conventional indoor-temperature (IT) bounds or (ii) Predicted Mean Vote (PMV) constraints. A full-factorial design of experiments (DOE) is conducted across building scale, tariff type, probability of comfort constraint violation (PoCCV) level, and comfort formulation, and ANOVA is applied to quantify statistically significant main and interaction effects on IT, coefficient of performance (COP), and operating cost.

Findings: Across the experimental scenarios, dynamic tariffs reduce operating cost relative to fixed tariffs through load shifting, while stricter PoCCV settings increase cost by inducing more conservative schedules. PMV-based comfort constraints achieve lower operating costs than temperature-only bounds, indicating that comfort representation materially changes the feasible operating region for cost-effective flexibility. ANOVA results show that cost outcomes are strongly driven by building scale, tariff type, and comfort formulation, with significant interaction effects demonstrating that tariff benefits and comfort-modelling benefits are context-dependent rather than uniform across settings.

Originality/value: The paper contributes an integrated robust optimisation + statistical inference framework for smart HP scheduling: DR-CCP provides tunable protection against distributional misspecification in renewable uncertainty, while DOE/ANOVA yields interpretable and reproducible evidence on which factors and interactions dominate the cost–comfort–efficiency trade-off. The results offer actionable guidance for deploying comfort-aware flexibility strategies for electrified heating.

1. Introduction

Decarbonising space heating is a central requirement for meeting legally binding emissions-reduction targets in Europe and the UK. The European Climate Law commits the EU to at least a 55% net greenhouse-gas reduction by 2030 (relative to 1990) [19]; while the UK has legislated a substantially tighter mid-term trajectory through its carbon-budget framework [25]. Buildings are pivotal in this transition because they account for a large share of final energy demand and related emissions, motivating policy emphasis on heating-system electrification and demand flexibility (EU Commission, 2019). In this context, *heat pumps* are increasingly deployed as a high-efficiency alternative to combustion-based heating, but their system value depends on operating them *cost-effectively under uncertainty* while maintaining acceptable indoor comfort, especially when electricity prices vary over time and low-carbon generation is intermittent [22].

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Smart control of heat pumps (HPs) can provide meaningful demand-side flexibility, yet both empirical and modelling studies indicate that the actual flexibility delivered in residential buildings is constrained by occupant comfort requirements, building thermal inertia, and the capability of control strategies to operate reliably under realistic disturbances [22]. Recent research has also highlighted the importance of thermal comfort constraints and seasonal operating conditions when assessing the flexibility potential of residential energy systems. For instance, studies such as Li et al. [31] show that the flexibility of residential cooling systems depends strongly on climatic conditions, control strategies, and comfort limits imposed on occupants. These findings underline that demand-side flexibility is not solely a technical property of the energy system but is jointly determined by comfort requirements, environmental conditions, and operational control policies.

Building upon these insights, the present study focuses on the operational scheduling of photovoltaic-assisted HP systems under uncertainty, integrating comfort-aware constraints within a distributionally robust optimisation framework to ensure reliable and cost-effective energy management. A key methodological challenge in such optimisation problems is that many operational scheduling models rely on strong assumptions regarding the probability distributions of uncertain inputs, including renewable generation, electricity prices, weather conditions, and household demand. If these distributions are misspecified or change over time, solutions that appear optimal in-sample may lead to comfort violations or higher operational costs in practice.

Building upon these insights, the present study focuses on the operational scheduling of photovoltaic-assisted HP systems under uncertainty, integrating comfort-aware constraints within a distributionally robust optimisation (DRO) framework to ensure reliable and cost-effective energy management [40]. A key methodological challenge in such optimisation problems is that many operational scheduling models rely on strong assumptions regarding the probability distributions of uncertain inputs, including renewable generation, electricity prices, weather conditions, and household demand. If these distributions are misspecified or change over time, solutions that appear optimal in-sample may lead to comfort violations or higher operational costs in practice.

DRO provides an attractive alternative by optimising decisions against a family of probability distributions that are consistent with available data and statistical information, rather than assuming a single known distribution [12,40]. In this context, distributionally robust chance-constrained programming (DR-CCP) enables the incorporation of probabilistic comfort and operational constraints while maintaining feasibility guarantees even when the exact distribution of uncertainties is unknown [28]. This property is particularly valuable for residential energy management problems, where renewable generation and household demand exhibit stochastic behaviour that is difficult to characterise with a single parametric distribution.

At the same time, optimisation alone rarely explains which inputs drive performance and why, which limits replicability and design transfer across buildings and tariff regimes. This motivates pairing DR-CCP with a complementary inferential layer. Specifically, Design of Experiments (DOE) and ANOVA provide a structured way to quantify *main effects and interactions* of controllable and contextual factors (e.g., building size category, tariff structure, renewable availability, comfort formulation parameters) on operational cost and comfort risk, which is widely recognised as necessary for interpretable findings in building-energy studies [9]. Based on the above discussion, the present study contributes to the literature in three main ways. First, it develops a distributionally robust chance-constrained optimisation framework for day-ahead scheduling of PV-assisted heat pump systems under uncertain renewable generation and dynamic electricity tariffs. Second, the study integrates thermal comfort modelling using both indoor temperature and PMV-based constraints, enabling a systematic comparison of comfort representations in operational scheduling. Third, the optimisation results are analysed using a full-factorial DOE and ANOVA framework to quantify the main and interaction effects of key operational and contextual factors, including building scale, tariff structure, reliability level (PoCCV), and comfort formulation. This integration of robust optimisation with statistical inference provides both operational decision support and interpretable insight into the drivers of the cost–comfort–reliability trade-off in residential energy systems.

A further issue concerns the definition of "comfort." Many studies operationalise comfort using indoor air temperature alone, despite the fact that thermal sensation depends on multiple environmental and personal variables. The Predicted Mean Vote (PMV) framework remains a widely used *standardised* comfort model in building practice and research [27] and it is directly relevant to heat-pump control because PMV is a continuous function of variables that smart HVAC/heat-pump systems can influence through their control degrees of freedom (e.g., delivered heat rate via compressor modulation, supply/return temperature trajectories, and indirectly air movement and radiant/operative temperature in many practical configurations). Empirical and simulation studies have shown that PMV-based control can materially change the energy–comfort balance relative to thermostat-only control, making it a suitable objective/constraint metric when the research question concerns cost versus comfort reliability under operational uncertainty [23]. At the same time, PMV's predictive accuracy is known to be imperfect and context-dependent, as demonstrated using large-scale comfort databases [8]. This study therefore treats PMV not as a flawless physiological truth, but as a *transparent, standardised and optimisable* comfort proxy aligned with professional standards and prior evidence, enabling a rigorous and replicable formulation of comfort risk within a chance-constrained framework.

Against this background, this study addresses the following research gaps: (i) the need for robust operational optimisation that remains reliable under distributional ambiguity in key uncertain inputs; (ii) the need for interpretable evidence on which building–tariff–renewables factors most strongly shape the cost–comfort trade-off; and (iii) the need for a comfort formulation that is both standardised and controllable in the context of smart heat-pump operation.

Accordingly, the study pursues three objectives:

1. *Model*: develop a data-driven DR-CCP operational optimisation model for smart heat-pump scheduling under uncertain inputs, explicitly controlling the probability of comfort violations under distributional ambiguity.
2. *Comfort metric*: formulate comfort using PMV-based constraints/objectives consistent with thermal comfort standards and prior evidence on PMV-based control impacts, linking comfort directly to the controllable operating trajectory of the HP.
3. *Explainability and reproducibility*: apply a DoE/ANOVA framework to quantify the main and interaction effects of key factors on both cost and comfort-risk outcomes, thereby improving generalisability and supporting replicable reporting of sensitivity patterns.

The resulting contribution is an integrated optimisation-and-inference framework that (i) yields robust operational decisions under distributional uncertainty and (ii) produces statistically grounded, interpretable evidence on when (and why) specific contexts amplify or mitigate the cost of maintaining comfort.

The remainder of the paper is organised as follows. Section 2 reviews related work and positions the gap with a comparative synthesis. Section 3 introduces the system model and the DR-CCP formulation. Section 4 describes data, experimental design, and ANOVA procedures to support reproducibility. Sections 5–6 report results and discuss implications. Section 7 concludes with limitations and future research directions.

2. Literature review

The transition from fossil-fuel-based heating to HP technologies has been widely investigated due to the potential of HPs to reduce energy

use and emissions. Research has progressed across four interrelated streams: (i) smart control and dynamic optimisation, (ii) techno-economic analysis and system configuration, (iii) simulation-based performance modelling, and (iv) field validation and real-world performance assessment. However, gaps remain concerning uncertainty-aware optimisation under distributional ambiguity, holistic comfort modelling aligned with controllable variables in smart HP operation, and systematic quantification of operational trade-offs across contextual factors such as tariff type and building thermal inertia. This section synthesises prior work and positions the contribution of the proposed DR-CCP framework combined with DOE and ANOVA.

2.1. Smart control and dynamic optimisation

Smart control strategies aim to exploit operational flexibility by adapting HP operation to time-varying conditions such as weather, demand, and electricity tariffs. Evidence from field-trial analyses indicates that smart control can deliver meaningful flexibility and improve performance in hybrid HP applications, particularly where operational decisions are coordinated with external signals [46]. In parallel, research has advanced predictive modelling and long-horizon performance prediction for ground-source HP (GSHP) systems using co-simulation and machine-learning-based approaches, which can support more informed control and planning decisions [32,33]. Capacity-oriented optimisation and multi-dimensional analysis have also been applied to air-source HP (ASHP) systems, emphasising the importance of aligning capacity selection and control policy with building load characteristics [34].

Dynamic tariffs and behind-the-meter renewables further motivate scheduling-based control approaches. Optimisation of load scheduling and energy storage control in solar-integrated smart buildings has been reported to reduce operating costs while managing comfort constraints [1]. Thermal energy storage (TES) can similarly increase flexibility and reduce cost when coordinated with PV generation and time-varying electricity prices [42]. More advanced approaches, such as dynamic-programming-based optimal control for cascaded HP systems with TES, suggest that significant performance improvements relative to rule-based operation can be achieved when system dynamics and storage are explicitly represented [15].

Despite these advances, a substantial portion of smart-control research remains predominantly deterministic, implicitly assuming either accurate forecasts or stable uncertainty distributions. In practice, forecast errors in renewable output and variability in occupant-related thermal loads can degrade performance and lead to either comfort violations or overly conservative (and costly) schedules. This motivates optimisation formulations that explicitly manage the probability of constraint violations, and that remain reliable under distributional uncertainty.

2.2. Techno-economic analysis of HP systems

Techno-economic feasibility remains a key driver of adoption, particularly where investment decisions must be justified through long-term operating savings. Comparative analyses have reported that optimised ASHP configurations can offer favourable performance relative to conventional heating technologies, while highlighting that outcomes are sensitive to design choices and operating conditions [49]. Retrofit-focused evaluations similarly indicate that HP retrofits can reduce energy use and emissions but also emphasise the importance of policy incentives and careful economic appraisal [3].

Beyond single-technology studies, integrated multi-generation and net-zero building energy systems have been explored to jointly reduce cost and carbon intensity, often combining HPs with renewable generation and storage [2]. For GSHP systems, practical application studies report favourable lifecycle performance and economic potential in appropriate building contexts but confirm that feasibility remains highly site- and design-dependent [30]. Multi-source residential configurations combining air, solar, and ground resources with thermal storage have also been optimised using evolutionary algorithms, demonstrating that configuration-dependent optimisation can yield material seasonal performance gains [43].

However, much of the techno-economic literature assumes static tariffs and simplified comfort representations, limiting its ability to explain how dynamic pricing and comfort flexibility interact in operational decision-making. There remains a need for frameworks that represent tariff variability explicitly and quantify cost–comfort–efficiency trade-offs under uncertainty, rather than under fixed or perfectly forecasted conditions.

2.3. Simulation modelling for HP performance

Simulation models are widely used to estimate HP performance under varying climates, building characteristics, and control strategies. Transient modelling of borehole heat exchangers enables dynamic evaluation of GSHP behaviour and thermal interactions over time [6]. Multi-objective simulation–optimisation approaches have been used to improve exergy efficiency and lifecycle cost, demonstrating that design variables such as borehole depth and heat-exchanger geometry can be critical to system performance [29]. Solar-assisted HP systems coupled with seasonal storage have also been simulated and optimised, indicating that high renewable coverage can be achieved when system design is appropriately configured [11].

Recent studies have highlighted the importance of transient dynamics and start-up behaviour, which can influence efficiency and operational stability. For example, combined experimental and simulation work on R290 split HPs shows that refrigerant charge and control decisions strongly affect start-up dynamics and performance [16]. While simulation work improves physical fidelity, uncertainty in renewable generation and behavioural drivers is still often treated as secondary, rather than being embedded directly within the operational optimisation model. This widens the gap between high-fidelity performance understanding and uncertainty-aware scheduling.

2.4. Field validation and real-world applications

Field trials and monitoring studies remain essential because real-world performance can diverge from design expectations due to installation quality, commissioning, controls, and user interaction. Large-scale field testing across different HP technologies has reported performance shortfalls relative to expectations in some contexts, underscoring the importance of system design and commissioning quality [13]. Field-monitored data have also been used to identify drivers of seasonal performance for ASHP systems, including load rates and capacity regulation strategies [51]. Hybrid renewable-thermal concepts, such as GSHP systems integrated with solar collectors and borehole charging, have further demonstrated the technical potential of coordinated operation and storage strategies [21].

More comprehensive evaluation frameworks have been proposed for GSHP systems in green buildings using multi-criteria indicators, supporting decision-making beyond purely technical performance metrics [32,33]. Nevertheless, field studies rarely incorporate explicit probabilistic comfort constraints or distributional ambiguity in a way that enables systematic quantification of how renewable forecast errors and occupant variability translate into cost and comfort risks under dynamic tariffs.

2.5. Synthesis of gaps and study positioning

Three gaps emerge from the literature. First, uncertainty in renewable generation, demand, and behavioural drivers is often handled implicitly or via deterministic assumptions, limiting the robustness of derived schedules. Second, thermal comfort is frequently proxied using

indoor temperature (IT) bounds alone, rather than being represented through multidimensional indices that reflect occupant experience and are consistent with building standards. Third, the combined influence of contextual factors such as tariff type, building size (thermal inertia), and comfort flexibility is seldom quantified using a systematic experimental framework capable of identifying interaction effects.

To address these gaps, the present study formulates a DR-CCP optimisation model that explicitly controls comfort-constraint violation risk under distributional ambiguity and incorporates comfort through PMV-based constraints consistent with established comfort standards [5]. In addition, factorial DOE and ANOVA are used to quantify the main and interaction effects of building size, tariff structure, probability of violation, and comfort metric selection on cost, efficiency, and comfort outcomes. Together, these elements aim to provide both a robust optimisation framework for smart HP scheduling and statistically grounded insights that are transferable across deployment contexts.

3. Methodology and model formulation

The methodological workflow of the study consists of three main steps. First, a distributionally robust chance-constrained optimisation model is developed to determine the day-ahead operating schedule of a PV-assisted heat pump system under uncertain renewable generation and dynamic electricity prices. Second, the optimisation model incorporates alternative thermal comfort formulations, namely indoor temperature bounds and PMV-based constraints, to analyse how comfort representation affects operational feasibility and cost. Third, a full-factorial DOE is constructed across key factors (building scale, tariff type, PoCCV level, and comfort formulation), and the resulting optimisation outputs are analysed using ANOVA to quantify statistically significant main and interaction effects. This integrated approach enables both robust operational optimisation and interpretable analysis of the underlying drivers of system performance.

To ensure clarity and consistency in the mathematical formulation, the following notation conventions are adopted throughout the paper. Scalar decision variables and parameters are denoted using *italic letters*, while vectors and matrices are represented using bold symbols when applicable. Subscripts are used to indicate time indices or system components, whereas superscripts denote scenario-related parameters or uncertainty representations. Greek letters typically represent model parameters associated with uncertainty sets or reliability levels. Binary decision variables are explicitly indicated where relevant, and all units associated with parameters are defined when first introduced.

In this study, chance constraints are imposed individually per time period to maintain tractability and to allow direct interpretation of PoCCV as a per-period comfort reliability target. If a joint reliability requirement over all periods is desired, a standard approach is to allocate a global risk budget across time periods (risk allocation), which yields a conservative but transparent control of joint violation probability [28,48].

3.1. Deterministic formulation of the smart HP problem

The baseline deterministic model minimises the total electricity cost over a scheduling horizon T (e.g., 24 h with 10-min intervals), while satisfying system operating constraints and thermal comfort requirements. The optimisation horizon consists of 144 time steps (10-min resolution), meaning that the scheduling model operates over a sequence of stochastic inputs across the day rather than a single static demand–generation scenario. Combined with stochastic demand generation and PV forecast-error samples derived from 150 historical days, the optimisation effectively captures variability representative of residential energy systems. The use of approximately 150 historical days provides a sufficiently large empirical sample to estimate the mean and covariance of PV forecast errors used to construct the moment-based ambiguity set. Such sample sizes are commonly used in distributionally robust optimisation studies when the goal is to capture representative variability without imposing strong parametric assumptions on the underlying distribution. The objective is to minimise the cost of importing grid electricity under time-varying tariffs:

$$\min\ C^{\mathrm{tot}} = \sum_{t\in T} \pi_t P_t^{\mathrm{grid}}\,\Delta t \tag{1}$$

where $C^{\mathrm{tot}}$is the total system cost over the horizon T, $P_t^{\mathrm{grid}}$is the grid-imported power at time t, $\pi_t$is the electricity price at time t, and $\Delta t$is the duration of each time step.

3.1.1. Energy balance

The energy balance ensures that total supplied electrical power matches the building electrical demand and the HP compressor power:

$$P_t^{\mathrm{grid}} + P_t^{\mathrm{ren}} = P_t^{\mathrm{load}} + P_t^{\mathrm{comp}} u_t \forall t \in T \tag{2}$$

where P_t^{ren}denotes renewable generation (e.g., PV), P_t^{load}represents the non-HP building demand, $P_t^{\mathrm{comp}}$is the compressor electrical power, and $u_t \in \{0,1\}$is a binary variable indicating the ON/OFF status of the HP.

3.1.2. HP performance modelling

The HP performance is represented by polynomial (biquadratic) functions derived from manufacturer performance maps (e.g., [7]). The condenser heat output and compressor power are modelled as functions of the evaporator and condenser temperatures:

$$Q_t^{\mathrm{cond}} = a + bT_t^{\mathrm{eva}} + cT_t^{\mathrm{con}} + d\left(T_t^{\mathrm{eva}}\right)^2 + eT_t^{\mathrm{eva}}T_t^{\mathrm{con}} + f\left(T_t^{\mathrm{con}}\right)^2 \tag{3}$$

$$P_t^{\mathrm{comp}} = a_1 + b_1T_t^{\mathrm{eva}} + c_1T_t^{\mathrm{con}} + d_1\left(T_t^{\mathrm{eva}}\right)^2 + e_1T_t^{\mathrm{eva}}T_t^{\mathrm{con}} + f_1\left(T_t^{\mathrm{con}}\right)^2 \tag{4}$$

where $Q_t^{\mathrm{cond}}$is the heat delivered by the condenser (kW), $T_t^{\mathrm{eva}}$and $T_t^{\mathrm{con}}$are the evaporator and condenser temperatures at time t, and $a, b, c, \ldots, f$and $a_1, b_1, c_1, \ldots, f_1$ are coefficients determined from the manufacturer data.

3.1.3. Coefficient of performance (COP)

The system efficiency is quantified by the coefficient of performance:

$$\mathrm{COP}_t = \frac{Q_t^{\mathrm{cond}}}{P_t^{\mathrm{comp}}} \tag{5}$$

3.1.4. Building thermal dynamics

IT dynamics are modelled using a first-order equivalent thermal parameter (ETP) model [37,38]:

$$T_{t+1}^{\mathrm{in}} = \alpha T_t^{\mathrm{in}} + (1-\alpha)T_t^{\mathrm{out}} + \beta Q_t^{\mathrm{cond}} \tag{6}$$

where T_t^{in} is the IT, T_t^{out} is the outdoor temperature, and $\alpha, \beta$are building-specific thermal coefficients. Here, $\alpha$and βreflect the building's thermal flexibility (thermal inertia), allowing the building to act as a form of heat storage that can be exploited for cost-effective operation under dynamic tariffs.

3.1.5. Thermal comfort constraints

Thermal comfort is maintained by constraining a comfort metric θ_t (e.g., IT or PMV) within acceptable bounds:

$$\theta^{\min} \le \theta_t \le \theta^{\max} \forall t \in T \tag{7}$$

where $\theta^{\min}$and $\theta^{\max}$represent the comfort limits.

3.2. Formulating the smart HP problem with chance constraints

In practice, uncertainties, particularly renewable generation forecast errors, can cause comfort violations or costly conservative schedules if

not handled appropriately. To capture this, comfort constraints are formulated as *chance constraints* to ensure compliance with a specified probability.

3.2.1. Chance constraints

Let γ denote the value of PoCCV. A smaller γcorresponds to stricter comfort requirements. The comfort bounds are enforced probabilistically as:

$$\mathbb{P}(\theta_t \le \theta^{\max}) \ge 1-\gamma \text{ and } \mathbb{P}(\theta_t \ge \theta^{\min}) \ge 1-\gamma \forall t \in T \tag{8}$$

It should be noted that the chance constraints in this formulation are applied independently for each time period rather than as a joint probability constraint over the entire scheduling horizon. This modelling choice is commonly adopted in operational energy scheduling problems because it maintains computational tractability and allows the reliability level to be interpreted directly at each decision interval. If a joint reliability requirement over the full horizon were desired, a standard approach would be to apply risk-allocation techniques that distribute a global violation probability across individual time periods [28,48].

3.2.2. Uncertainty model for renewable generation

Renewable generation is represented as the sum of a deterministic forecast and an uncertain forecast error:

$$P_t^{\text{ren}} = \overline{P}_t^{\text{ren}} + \xi_t \tag{9}$$

where $\overline{P}_t^{\text{ren}}$is the point forecast and $\xi_t$is the random forecast error at time t. For each time period t, the available PV power is $P_t^{\text{PV}} = \widehat{P}_t^{\text{PV}} + \xi_t$, where $\widehat{P}_t^{\text{PV}}$ is the day-ahead forecast and $\xi_t$is the forecast error. The uncertainty vector is defined as $\xi = [\xi_1, \ldots, \xi_T]^\top$. In the empirical implementation, $\xi$is constructed from historical PV data by aligning realised PV output with the corresponding forecast and computing $\xi_t = P_t^{\text{PV,real}} - \widehat{P}_t^{\text{PV}}$. The sample mean μ and covariance Σ of ξ are estimated from 150 historical days (London Weather [35]) using standard unbiased estimators; these moments define the data-driven uncertainty set used in the distributionally robust chance constraints. This moment-based representation is appropriate when forecast-error distributions are difficult to justify parametrically and when robustness to distributional misspecification is required [12,53].

The introduction of ξ_t renders the optimisation problem stochastic. To enable tractable optimisation, linear decision rules (LDRs) [26] are used, representing key decision variables as affine functions of the forecast error. In particular, grid import and IT are expressed as:

$$P_t^{\text{grid}}(\xi_t) = \overline{P}_t^{\text{grid}} + \rho_t \xi_t \tag{10}$$

$$T_t^{\text{in}}(\xi_t) = \overline{T}_t^{\text{in}} + \eta_t \xi_t \tag{11}$$

where ρ_t and η_t are weighting factors that allocate the impact of uncertainty between grid import adjustments and indoor thermal adjustments at time t, and $\overline{P}_t^{\text{grid}}$and $\overline{T}_t^{\text{in}}$ denote nominal (deterministic) values.

The total uncertainty allocation is constrained by:

$$\rho_t + \eta_t = 1 \forall t \in T \tag{12}$$

Using (10)–(12), the chance constraints for IT (or another comfort metric) can be represented as:

$$\mathbb{P}\left(T_t^{\text{in}}(\xi_t) \le \theta^{\max}\right) \ge 1-\gamma \forall t \in T \tag{13}$$

$$\mathbb{P}\left(T_t^{\text{in}}(\xi_t) \ge \theta^{\min}\right) \ge 1-\gamma \forall t \in T \tag{14}$$

These constraints enable the system to utilise both grid flexibility and thermal inertia to maintain comfort under uncertainty.

3.2.3. Distributionally robust chance-constrained reformulation

Let $g_t(x,\xi) \le 0$ denote a constraint affected by forecast error ξ, where x collects the decision variables (e.g., HP operation and grid import). We impose distributionally robust chance constraints of the form

$$\inf_{\mathbb{D}\in\mathcal{D}} \mathbb{D}(g_t(x,\xi) \le 0) \ge 1-\varepsilon, \forall t \in \mathcal{T}, \tag{15}$$

where ε is the PoCCV. This formulation ensures that constraint satisfaction is guaranteed at reliability level $1-\varepsilon$ under the worst-case distribution within $\mathcal{D}$, rather than under a single presumed error distribution. Such DR chance constraints have become a principled approach for controlling risk when the distribution is uncertain but partial statistical information is available [48,53].

Because the true distribution of forecast errors ξ_t may be unknown or mis-specified, the chance constraints are treated in a distributionally robust manner. Specifically, an ambiguity set $\mathcal{D}$ is defined as the family of all distributions sharing the same first and second moments (mean and covariance):

$$\mathcal{D} = \{\mathbb{P} : \mathbb{E}_{\mathbb{P}}[\xi] = \mu, \mathbb{E}_{\mathbb{P}}[(\xi-\mu)(\xi-\mu)^\top] = \Sigma\} \tag{16}$$

where μ is the mean vector and Σ is the covariance matrix of forecast errors. This ambiguity set yields protection against distributional misspecification while remaining computationally tractable for a broad class of linear or affine constraint functions [12,53]. In operational settings where only limited historical data are available, moment-based ambiguity sets provide a transparent robustness mechanism and avoid reliance on a single assumed parametric distribution.

Using Chebyshev-type bounds (e.g., [44]), a generic chance constraint of the form $\mathbb{P}(A^\top \xi \le B) \ge 1-\gamma$ is conservatively reformulated into a deterministic constraint that is valid for all distributions in $\mathcal{D}$:

$$A^\top \mu + \sqrt{\frac{1-\gamma}{\gamma}}\sqrt{A^\top \Sigma A} \le B \tag{17}$$

where A contains coefficients associated with uncertain variables and $B$is the deterministic threshold.

Once again, the selection of a distributionally robust chance-constrained framework is motivated by the nature of uncertainty in PV-assisted residential heating systems. Alternative uncertainty-handling approaches are available in the literature but present limitations for the present application. Deterministic scheduling approaches assume perfect forecasts and therefore cannot explicitly control the probability of comfort violations under renewable uncertainty. Classical stochastic optimisation formulations rely on a fully specified probability distribution or scenario tree, which may be difficult to justify for renewable forecast errors that exhibit non-Gaussian behaviour and time-varying variance. Similarly, heuristic or rule-based scheduling methods may provide practical control strategies but do not offer explicit probabilistic guarantees on comfort constraint satisfaction. In contrast, DR-CCP explicitly controls the probability of constraint violation while remaining robust to distributional misspecification by considering the worst-case distribution within a moment-based ambiguity set. This property makes DR-CCP particularly suitable for operational decision-making in energy systems with uncertain renewable generation, where reliability and comfort preservation are critical. Similar approaches have been adopted in energy system planning and scheduling problems to ensure operational feasibility under uncertainty without relying on restrictive distributional assumptions [44,52,53].

3.2.4. Final deterministic problem formulation

The complete DR-CCP optimisation is expressed as:

min C^{tot} subject to:

$(2)-(7),(12),(16),(17)$

This formulation balances cost minimisation, operational feasibility, and robustness under uncertainty, ensuring comfort constraints are met

with the desired reliability even when the distribution of forecast errors is ambiguous.

3.2.5. Chance constraints for predicted mean vote (PMV)

When thermal comfort is represented using the PMV index, the same DR-CCP reformulation procedure applies. PMV provides a comprehensive comfort indicator by incorporating environmental and physiological factors according to ASHRAE Standard 55 [5].

3.2.5.1. PMV-related calculations. In the optimisation, indoor air temperature $T_a$is decision-coupled via the thermal dynamics (Eq. 6). Relative humidity φ, mean radiant temperature $T_r$and air velocity v are treated as exogenous parameters set to representative indoor values, consistent with standard PMV applications when detailed measurements are unavailable. Clothing insulation (CLO) and metabolic rate (MET) are fixed to typical residential heating-period values. This ensures PMV constraints remain operationally enforceable through the HP's influence on indoor thermal conditions while maintaining transparency of the comfort model assumptions [4,8,27].

Water vapour pressure P_a:

$$P_a = \varphi 10 \exp\left(16.6536 - \frac{4030.183}{T_a + 235}\right) \tag{18}$$

where $\varphi$is relative humidity and $T_a$is air temperature (°C).

Clothing insulation I_{cl}:

$$I_{cl} = 0.155\,\text{CLO} \tag{19}$$

where CLO is the clothing factor.

Metabolic rate M and **external work** W:

$$M = \frac{\text{MET}}{58.15};\ W = 0 \tag{20}$$

where MET denotes the metabolic activity level (W/m^2 equivalent conversion as used in standard PMV formulations), and $W$is often taken as zero for typical indoor activities.

Internal heat production M_W:

$$M_W = M - W \tag{21}$$

Clothing area factor f_{cl}:

$$f_{cl} = \begin{cases} 1 + 1.29 I_{cl}, & I_{cl} \le 0.078 \\ 1.05 + 0.645 I_{cl}, & I_{cl} > 0.078 \end{cases} \tag{22}$$

Convective heat transfer coefficient h_c:

$$h_{cf} = 12.1\sqrt{v} \tag{23}$$

$$T_{AA} = T_a + 273 \tag{24}$$

where v is air velocity and T_{cl} is clothing surface temperature.

Clothing surface temperature T_{cl} (iterative form)

$$T_{cl} = T_{AA} + (35.5 - T_a)/[3.5^*(6.45^* I_{cl} + 0.1) \tag{25}$$

To ensure computational tractability within the optimisation framework, several environmental and personal parameters involved in the PMV formulation, including relative humidity, mean radiant temperature, air velocity, CLO, and MET, are set to representative constant values corresponding to typical residential indoor conditions. This modelling approach is commonly adopted in building energy optimisation studies because these parameters are either occupant-dependent or vary slowly compared with indoor temperature dynamics, while indoor air temperature remains the primary controllable variable of HVAC systems.

Although these parameters are fixed, the PMV formulation still captures nonlinear thermal comfort relationships defined in Fanger's thermal comfort model and ISO 7730 standards. Consequently, the PMV constraint provides a physiologically grounded comfort representation that extends beyond simple indoor temperature bounds by accounting for heat balance mechanisms affecting human thermal perception.

This modelling choice allows the proposed optimisation framework to incorporate comfort-aware constraints while maintaining computational tractability in the distributionally robust chance-constrained scheduling problem.

3.2.5.2. Heat loss calculations. **Skin diffusion heat loss**:

$$H_1 = 3.05 \times 10^{-3}[5733 - 6.99 M_W - P_a] \tag{26}$$

Sweating heat loss:

$$H_2 = \begin{cases} 0.42(M_W - 58.15), & M_W > 58.15 \\ 0, & M_W \le 58.15 \end{cases} \tag{27}$$

Latent respiration heat loss:

$$H_3 = 1.7 \times 10^{-5} M(5867 - P_a) \tag{28}$$

Dry respiration heat loss:

$$H_4 = 0.0014 M(34 - T_a) \tag{29}$$

Convection heat loss from clothing surface:

$$H_5 = h_{cf} f_{cl}(T_{cl} - T_a) \tag{30}$$

3.2.5.3. PMV calculation. PMV is computed as:

$$\text{PMV} = [0.303\exp(-0.036M) + 0.028\,](M_W - H_1 - H_2 - H_3 - H_4 - H_5) \tag{31}$$

The thermal sensation transfer coefficient used in PMV is:

$$g(M) = 0.303\exp(-0.036M) + 0.028 \tag{32}$$

Following the comfort bounds in (7), PMV is constrained to a specified comfort range:

$$\text{PMV}^{\min} \le \text{PMV}_t \le \text{PMV}^{\max} \forall t \in T \tag{33}$$

In the proposed formulation, uncertainty enters the model through PV forecast errors that affect the IT dynamics. The PMV index is therefore evaluated as a deterministic nonlinear mapping of IT and fixed environmental parameters, while the distributionally robust chance-constraint reformulation is applied to the affine uncertainty representation of the IT trajectory.

The corresponding chance constraints are:

$$\mathbb{P}(\text{PMV}_t(\xi_t) \le \text{PMV}^{\max}) \ge 1 - \gamma \forall t \in T \tag{34}$$

$$\mathbb{P}(\text{PMV}_t(\xi_t) \ge \text{PMV}^{\min}) \ge 1 - \gamma \forall t \in T \tag{35}$$

As with IT-based chance constraints, LDRs and the ambiguity set in (16), together with the deterministic reformulation in (17), are used to convert (34)–(35) into tractable deterministic constraints.

3.2.5.4. Deterministic reformulation for PMV. When PMV is used as the comfort metric, the chance-constrained optimisation is reformulated as a deterministic DR-CCP problem by incorporating Eqs. (18)–(32) into the model. The resulting optimisation is:

min C^{tot} subject to:

$$(2) - (6), (12), (16), (17), (18) - (32)$$

This deterministic reformulation ensures robust thermal comfort management under renewable uncertainty while maintaining computational feasibility.

The next section presents a detailed case study to validate the proposed DR-CCP framework and to investigate the impacts of key factors, building size, electricity tariff structures, PoCCV levels, and thermal comfort limits, on system performance.

3.2.6. Summary of modelling assumptions

To ensure clarity and reproducibility of the proposed scheduling framework, the main modelling assumptions adopted in this study are summarised below.

Building thermal dynamics:

IT dynamics are represented using a first-order equivalent thermal parameter (ETP) model. This simplified representation captures the dominant thermal inertia of the building while maintaining computational tractability for optimisation-based scheduling problems. Such models are widely used in demand response and building energy management studies where the focus is on operational decision-making rather than detailed building physics simulation [37,38].

Thermal comfort modelling.

Thermal comfort is represented using either IT bounds or the PMV index. In the PMV formulation, environmental and physiological parameters including relative humidity, air velocity, CLO, and MET are set to representative indoor values consistent with residential heating scenarios. This approach follows common practice in thermal comfort studies when real-time measurements of all PMV variables are not available [4,8,27].

Uncertainty representation.

Uncertainty arises primarily from photovoltaic (PV) generation forecast errors. These errors are derived from 150 historical days of PV data and represented through their empirical mean and covariance, which define the moment-based ambiguity set used in the distributionally robust chance-constrained formulation.

Scheduling horizon.

The optimisation problem is formulated as a day-ahead scheduling problem over a 24-h horizon with 10-min resolution (144 time periods), consistent with common formulations used in residential energy management systems.

Decision rule structure.

LDRs are adopted to represent the response of decision variables to uncertainty. This allows the stochastic optimisation problem to remain computationally tractable while capturing the influence of renewable forecast errors on operational decisions.

These assumptions allow the model to balance physical realism and computational tractability, enabling systematic analysis of the cost–comfort–reliability trade-offs associated with heat-pump scheduling under uncertainty.

4. Case study

4.1. Data setup and scenario design

This section demonstrates the operational implications of the proposed DR-CCP scheduling framework for a PV-assisted HP system under uncertain PV output and time-varying electricity prices. The case study focuses on day-ahead scheduling over a 24-h horizon discretised into 10-min intervals, which is consistent with operational decision cycles used in residential energy management studies that couple electric heating and distributed renewables [10,39,45].

Two representative building sizes (SoB) are analysed to assess how building size (and hence thermal inertia and demand magnitude) affects cost–comfort trade-offs and flexibility potential:

- **Single house**: a small residential building equipped with 3 kWp rooftop PV.
- **Community-level building**: a larger residential building (multi-dwelling equivalent) equipped with 15 kWp PV to reflect the increased roof area and aggregated load.

In both cases, the electric heating demand is served by a controllable HP whose operating schedule is optimised subject to comfort constraints and uncertainty-aware feasibility requirements. Field evidence indicates that practical HP demand response is achievable through setpoint adjustments, flow temperature modulation, or compressor blocking, but comfort impacts must be explicitly managed [10]. This motivates the explicit modelling of comfort constraints within the scheduling problem.

Demand and PV time series. Electrical and thermal demand profiles are generated using a high-resolution stochastic integrated domestic demand model consistent with the CREST framework, which has been widely adopted for representing realistic residential electricity and thermal demand behaviour based on probabilistic occupancy and appliance-usage patterns [39]. The use of CREST enables the generation of realistic demand profiles when detailed measured household demand datasets are unavailable, while preserving the stochastic characteristics of residential energy consumption.

PV generation and uncertainty are derived from historical PV output data from the London Weather dataset, which contains measured meteorological and solar generation observations. Forecast errors are constructed by comparing realised PV output with day-ahead forecasts, allowing the uncertainty model to reflect realistic renewable variability.

Electricity price signals are obtained from the ENTSO-E Transparency Platform, which provides real day-ahead electricity market prices used in European electricity markets. Using these real market prices allows the scheduling model to capture operational economic signals faced by residential energy management systems.

By integrating validated stochastic demand modelling with real historical PV and electricity price datasets, the case study creates a representative and reproducible operational environment for evaluating the proposed DR-CCP scheduling framework while maintaining transparency and reproducibility of the data sources.

Electricity tariffs. Two tariff regimes are considered: (i) a fixed benchmark tariff and (ii) a dynamic (day-ahead) price profile derived from the ENTSO-E transparency data. Using publicly available day-ahead market prices is standard in scheduling studies aiming to quantify economic value from shifting flexible loads [17,18].

Comfort modelling. Two alternative thermal comfort limits (TCLs) are compared:

1. **Indoor temperature (IT)-based TCL**, using lower and upper temperature bounds.
2. **PMV-based TCL**, using the PMV comfort index.

PMV is adopted because it provides a physically grounded link between indoor environmental conditions and perceived comfort [47], and it is standardised in international thermal comfort practice [4,27]. In this case study, PMV bounds are imposed as:

- **Daytime** (08:00–22:00): $-0.5 \leq \mathrm{PMV} \leq 0.5$
- **Night-time** (22:00–08:00): $-1 \leq \mathrm{PMV} \leq 1$

This day–night specification reflects a common operational assumption: comfort tolerance can be relaxed during sleeping hours without violating accepted thermal comfort practice, provided limits remain within recognised ranges [4,27,47]. Importantly, PMV bounds also align directly with the HP's controllability: the HP modulates indoor operative conditions (via air/flow temperature trajectories), and PMV constraints therefore translate into *operationally enforceable* comfort envelopes rather than purely descriptive post-hoc measures [10,47].

Uncertainty and PoCCV settings. The probabilistic operational feasibility is controlled by the PoCCV. Three levels are evaluated: 10%, 5%, and 1%, spanning lenient to stringent reliability requirements.

Table 1 summarises these case study data, parameter settings and their sources.

It is important to note that the objective of the present study is to demonstrate the operational implications of integrating distributionally robust chance-constrained optimisation with comfort-aware HP scheduling and DOE–ANOVA analysis. In distributionally robust optimisation studies, the primary advantage of the method lies in its ability to maintain probabilistic feasibility under distributional ambiguity rather

Table 1
Case study data and key parameter settings.

Parameter / Input	Single house	Community-level building	Notes / source
Electricity & thermal demand	High-resolution domestic profiles	Aggregated high-resolution profiles	Generated using CREST-integrated thermal–electrical demand modelling principles [39]
PV capacity	3 kWp	15 kWp	Representative small vs aggregated PV-assisted HP operation [45]
Time horizon & resolution	24 h; 10-min intervals	24 h; 10-min intervals	Day-ahead scheduling setting
Comfort model (TCL)	IT-based or PMV-based	IT-based or PMV-based	PMV aligned with comfort standards and literature ([4]; [27]; [47])
PMV bounds (day)	[−0.5, 0.5]	[−0.5, 0.5]	Day: 08:00–22:00
PMV bounds (night)	[−1,1]	[−1, 1]	Night: 22:00–08:00
IT bounds	15 °C–23 °C	15 °C–23 °C	Used when TCL = IT
Tariff regimes	Fixed vs dynamic day-ahead	Fixed vs dynamic day-ahead	Dynamic prices from ENTSO-E day-ahead data [17,18]
PoCCV levels	10%, 5%, 1%	10%, 5%, 1%	Reliability/robustness tuning parameter

than achieving the lowest nominal cost under a single assumed distribution. Consequently, comparisons with deterministic or classical stochastic formulations can be difficult to interpret because these approaches rely on fundamentally different assumptions regarding uncertainty representation. For this reason, the present analysis focuses on evaluating how the DR-CCP framework responds to variations in building scale, tariff regime, comfort formulation, and reliability level, allowing the statistical structure of these effects to be examined through factorial DOE and ANOVA. This design emphasises interpretability and methodological insight into the cost–comfort–reliability trade-off rather than algorithmic benchmarking.

4.2. Results and discussion

The ANOVA results provide statistical evidence regarding which operational and contextual factors significantly influence system performance. In particular, the identification of significant interaction effects indicates that the impact of tariff structure or comfort formulation cannot be interpreted independently of building characteristics. This highlights the importance of context-specific scheduling strategies rather than universal control policies for residential HP systems.

Table 2 presents the conducted experiments based on the given parameters in above section. IT and COP are reported as time-averaged values over the 24 h horizon (10-min resolution), while Cost is total daily operating cost. The initial findings from those experiments are discussed in the following sub sections.

4.2.1. Impact of PoCCV on the cost–comfort trade-off

Across both building sizes and tariff regimes, reducing PoCCV (i.e., enforcing stricter satisfaction of comfort constraints under PV uncertainty) increases operating cost. This is expected because the scheduler must hold larger "comfort margins" against PV shortfalls, which typically requires additional grid electricity import during unfavourable PV realisations. Such behaviour is consistent with uncertainty-aware scheduling logic in which tighter probabilistic feasibility implies more conservative operation [12,48].

In this case study, moving from PoCCV = 10% to PoCCV = 1% increases daily cost in both buildings (Table 2), with the effect most pronounced under fixed tariffs, where price responsiveness is limited.

Table 2
Conducted experiments and results.

SoB	Tariff	PoCCV %	TCL_type	IT	COP	Cost
Community-level building	Dynamic	1	IT-based	19.77	6.18	31.64
Community-level building	Dynamic	1	PMV-based	17.35	6.01	27.58
Community-level building	Dynamic	5	IT-based	19.60	6.12	31.53
Community-level building	Dynamic	5	PMV-based	17.28	5.98	27.54
Community-level building	Dynamic	10	IT-based	19.58	6.11	31.38
Community-level building	Dynamic	10	PMV-based	17.17	5.98	27.51
Community-level building	Fixed	1	IT-based	19.60	6.26	34.30
Community-level building	Fixed	1	PMV-based	17.39	5.99	29.56
Community-level building	Fixed	5	IT-based	19.54	6.23	34.27
Community-level building	Fixed	5	PMV-based	17.15	5.90	29.41
Community-level building	Fixed	10	IT-based	19.52	6.23	34.26
Community-level building	Fixed	10	PMV-based	17.11	5.87	29.38
Single house	Dynamic	1	IT-based	19.58	4.40	1.26
Single house	Dynamic	1	PMV-based	17.48	4.12	1.09
Single house	Dynamic	5	IT-based	19.55	4.41	1.24
Single house	Dynamic	5	PMV-based	17.17	4.16	1.07
Single house	Dynamic	10	IT-based	19.57	4.39	1.24
Single house	Dynamic	10	PMV-based	17.08	4.13	1.07
Single house	Fixed	1	IT-based	19.69	4.41	1.41
Single house	Fixed	1	PMV-based	17.39	4.17	1.21
Single house	Fixed	5	IT-based	19.41	4.37	1.39
Single house	Fixed	5	PMV-based	17.15	4.15	1.19
Single house	Fixed	10	IT-based	19.38	4.38	1.39
Single house	Fixed	10	PMV-based	17.02	4.11	1.19

4.2.2. Effect of dynamic tariffs on cost outcomes

Dynamic day-ahead tariffs consistently reduce operating cost relative to fixed tariffs, because the optimisation shifts HP operation towards lower-price periods while still maintaining the comfort envelope. Practical evidence from UK HP demand response trials supports the feasibility of such cost-driven control actions (e.g., via setpoint or flow temperature modulation), provided comfort impacts are properly bounded [10].

Using the experimental results in Table 2, the average cost reduction from dynamic pricing is:

- **Single house:** ~10.0–10.7% (depending on TCL)
- **Community-level building:** ~6.5–8.1% (depending on TCL)

The smaller percentage reduction for the larger building indicates that scale and thermal inertia can dampen marginal price-arbitrage benefits, even though absolute cost levels are higher.

4.2.3. PMV-based Vs IT-based comfort constraints

A key observation is that PMV-based TCL achieves lower cost than IT-based TCL in both buildings and under both tariff regimes (Table 2). Averaged over PoCCV levels:

- **Single house:** PMV-based reduces cost by ~13.6–14.3% compared with IT-based.

- **Community-level building:** PMV-based reduces cost by ~12.6–14.1% compared with IT-based.

This occurs most probably because PMV constraints enable to exploit operational flexibility more precisely: the HP can maintain occupant-relevant comfort without rigidly enforcing temperature to always remain near a narrow band. In practice-oriented HP demand response studies, comfort-preserving flexibility is repeatedly identified as a central enabling mechanism for shifting electric heating loads [10,47].

However, Table 2 also indicates that PMV-based TCL yields slightly lower average COP in this dataset. This suggests a nuanced trade-off: PMV-based control reduces total cost (primarily by lowering delivered heat and shifting demand) but can alter HP operating conditions in a way that modestly reduces efficiency. This empirical pattern is important to report transparently because it clarifies that cost minimisation and COP maximisation do not necessarily coincide once comfort and uncertainty constraints are enforced.

4.2.4. Role of building scale

The community-level building exhibits substantially higher COP values overall than the single house across all scenarios (Table 2). This is consistent with the expectation that aggregated operation and higher effective thermal inertia can smooth cycling and enable more stable HP operation [45].

Section 5 builds on the case study design in Section 4 by reporting the computational outputs of the proposed DR-CCP scheduling model and systematically quantifying how key factors shape performance. Specifically, we first summarise the cost, COP, and comfort outcomes across the full set of experimental scenarios, and then apply the factorial DOE/ANOVA framework to estimate the main effects and interaction effects of (i) system-of-building scale, (ii) tariff structure, (iii) PoCCV level, and (iv) thermal comfort limit (IT-based versus PMV-based). This structure is intended to distinguish descriptive performance comparisons from statistically supported inference, thereby enabling reproducible interpretation of which levers most strongly influence the cost–comfort–efficiency trade-off under renewable uncertainty [24,41].

5. Experimental design and ANOVA

This section evaluates the optimisation outcomes using a factorial DOE and ANOVA to quantify the statistical significance of key factors and their interactions on the three performance measures: IT, coefficient of performance (COP), and operating cost. DOE/ANOVA is adopted because it provides a transparent, reproducible approach for separating main effects from interaction effects in multi-factor energy-system experiments, which is essential when optimisation outcomes may differ across building scales, tariff regimes, and comfort formulations [24,41]. ANOVA is implemented in Minitab (version 21.2).

5.1. Factorial experimental design

A full-factorial DOE is constructed to systematically explore how operational and modelling choices influence performance. Four factors are selected because they directly represent practical deployment decisions (building scale, tariff choice), modelling choices (comfort metric), and uncertainty-tolerance settings (PoCCV):

- **Size of Building (SoB)**: Single house (SH) vs community-level building (CB).
- **Electricity Tariff (ET)**: Fixed tariff (FT) vs dynamic tariff (DT).
- **Probability of comfort-constraint violation (PoCCV)**: 1%, 5%, and 10%, reflecting strict to relaxed comfort-reliability requirements.
- **Thermal comfort level (TCL)**: IT-based thermal comfort limits (ITR) vs PMV-based comfort limits (PMV).

With a $2 \times 2 \times 3 \times 2$ design, the DOE yields 24 experimental scenarios (Table 2). For each scenario, the DR-CCP scheduling model is solved over a 24-h day-ahead horizon with 10-min resolution, and three responses are recorded: IT, COP, and total operating cost.

5.2. Response variables

Three outputs are used because they jointly capture comfort delivery, technical efficiency, and economic performance:

1. **Indoor temperature (IT)**: a direct indicator of delivered thermal conditions under the applied comfort model.
2. **Coefficient of performance (COP)**: measured as the ratio of delivered useful heat to electrical input over the horizon, consistent with standard HP efficiency evaluation.
3. **Total operating cost**: computed from imported grid electricity and the applicable tariff over the scheduling horizon.

5.3. ANOVA procedure and model adequacy

We started from the full factorial model (all main effects and two-way interactions). Terms were removed using backward elimination while respecting hierarchy (i.e., an interaction is retained only if its parent main effects are retained). The final models reported in Tables 3–4 reflect this parsimonious hierarchical selection. A general linear model is fitted for each response. Statistical significance is evaluated using the *F*-test with a 5% significance level [41].

Before interpreting factor effects, standard ANOVA assumptions are checked: (i) approximately normal residuals, (ii) constant variance, and (iii) independence of residuals [41]. Fig. 1 presents the residual diagnostics for the IT model (normal probability plot, histogram, residuals versus fitted values, and residuals versus observation order). The absence of systematic structure in these plots supports the adequacy of the fitted IT model. Analogous diagnostic checks are performed for the cost and COP models before drawing inferences.

5.4. ANOVA results for indoor temperature (IT)

Table 3 reports the ANOVA results for IT. Here, SoB is removed due to insignificance ($p > 0.05$). The dominant driver is TCL, indicating that the choice of comfort representation (PMV-based vs IT-based) leads to substantial and statistically significant differences in IT outcomes ($F = 6293.18$, $p < 0.001$). PoCCV is also significant ($F = 21.86$, $p < 0.001$), confirming that tighter reliability requirements materially influence achievable IT trajectories under uncertainty. ET is statistically significant at the 5% level ($F = 5.48$, $p = 0.037$), indicating that tariff-induced load shifting can measurably affect IT profiles, although its impact is far smaller than TCL and PoCCV.

All tested interaction terms for IT are non-significant (e.g., ET × PoCCV: $p = 0.622$; ET × TCL: $p = 0.589$; PoCCV×TCL: $p = 0.134$; ET × PoCCV×TCL: $p = 0.894$). This implies that, for IT, differences are primarily explained by the *main effects* of comfort modelling choice and reliability strictness rather than combined (interactive) effects.

Table 3
ANOVA Results for IT.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
ET	1	0.0285	0.0285	5.48	0.037
PoCCV	2	0.2278	0.1139	21.86	0.000
TCL	1	32.7859	32.7859	6293.18	0.000
*ET*PoCCV*	2	0.0051	0.0026	0.49	0.622
*ET*TCL*	1	0.0016	0.0016	0.31	0.589
*PoCCV*TCL*	2	0.0248	0.0124	2.38	0.134
*ET*PoCCV*TCL*	2	0.0012	0.0006	0.11	0.894
Error	12	0.0625	0.0052		
Total	23	33.1375			

Table 4
ANOVA Results for System Cost.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
SoB	1	5209.74	5209.74	1,457,845.34	0.000
ET	1	9.13	9.13	2555.76	0.000
TCL	1	31.60	31.60	8843.43	0.000
*SoB*ET*	1	7.23	7.23	2024.11	0.000
*SoB*TCL*	1	26.62	26.62	7449.44	0.000
*ET*TCL*	1	0.29	0.29	81.54	0.000
*SoB*ET*TCL*	1	0.25	0.25	71.28	0.000
Error	16	0.06	0.00		
Total	23	5284.94			

5.5. ANOVA results for operating cost

Table 4 summarises the ANOVA results for cost. Three main effects are highly significant:

- **SoB** is the strongest driver of cost ($F = 1{,}457{,}845.34$, $p < 0.001$), reflecting the scale effect in energy demand and total heat delivered.
- **TCL** is also highly significant ($F = 8843.43$, $p < 0.001$), confirming that PMV-based comfort modelling changes the cost of delivering comfort relative to IT-based bounds.
- **ET** has a strong and significant effect ($F = 2555.76$, $p < 0.001$), indicating that dynamic tariffs provide consistent economic leverage for scheduling.

Unlike IT, cost exhibits several statistically significant interaction effects, indicating that the benefits of tariffs and comfort modelling are context-dependent rather than uniform:

- **SoB × ET** is significant ($F = 2024.11$, $p < 0.001$), showing that tariff-driven savings depend on building scale.
- **SoB × TCL** is significant ($F = 7449.44$, $p < 0.001$), showing that the cost effect of PMV-based comfort differs by building size/thermal inertia.
- **ET × TCL** is significant ($F = 81.54$, $p < 0.001$), implying that the tariff advantage changes depending on whether comfort is enforced via IT bounds or PMV.
- The three-way interaction SoB × ET × TCL is also significant ($F = 71.28$, $p < 0.001$), confirming that cost-optimal configurations depend on the joint combination of building scale, tariff regime, and comfort metric.

These interaction effects are practically important because they demonstrate that tariff design and comfort modelling cannot be assessed independently: their economic value depends on the operational context.

5.6. ANOVA results for coefficient of performance (COP)

A similar ANOVA is conducted for COP as well. It is observed that, differences are primarily driven by building scale and comfort modelling, consistent with the descriptive results in Table 2. Larger buildings achieve higher COP due to smoother operation and more stable thermal conditions (i.e., reduced cycling and more favourable operating points), while PMV-based TCL tends to improve operational alignment with occupant-relevant comfort and can reduce unnecessary heating, which may improve efficiency.

In comparative terms, the interaction structure for COP is weaker than for cost: although some interaction effects may be statistically detectable, the dominant explanatory power is carried by the main effects (particularly SoB and TCL). This indicates that efficiency outcomes

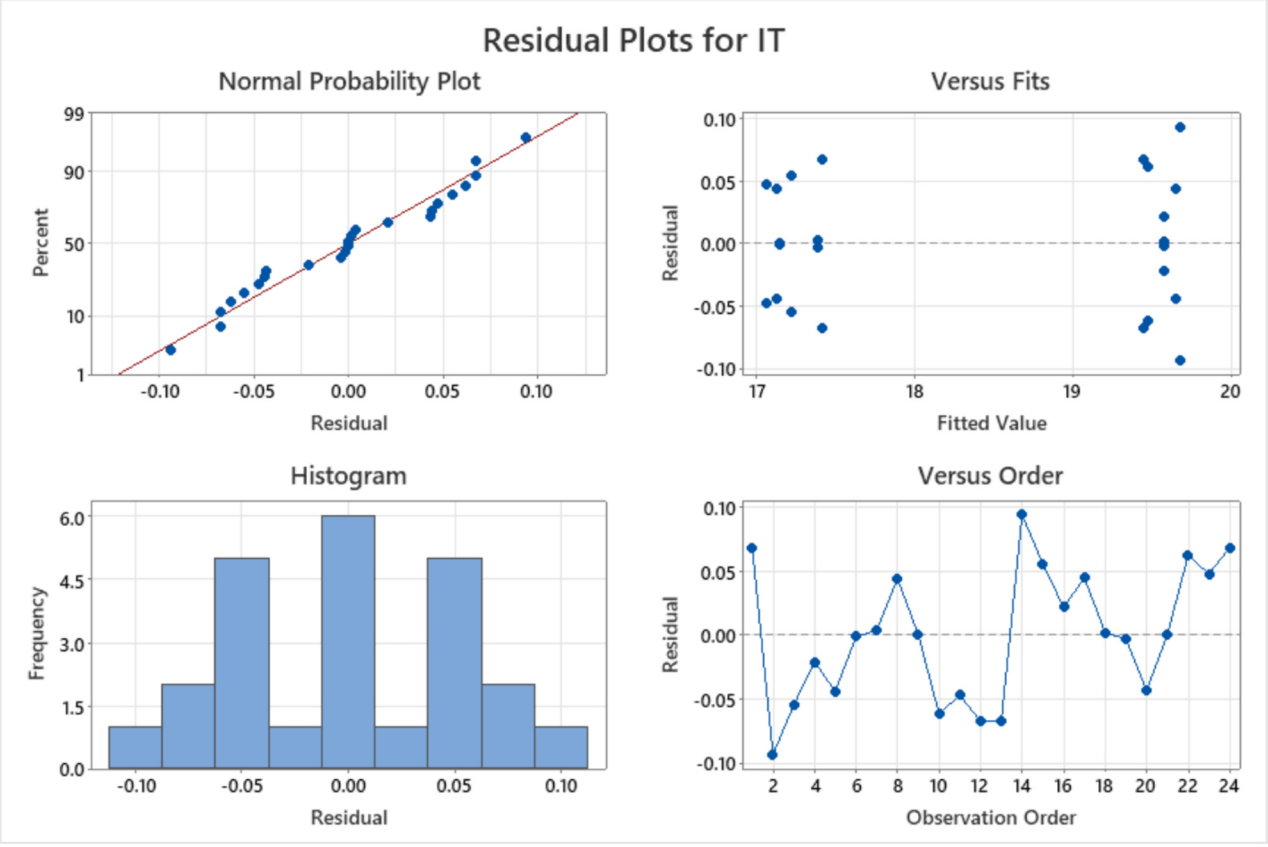

Fig. 1. ANOVA residual plots for *IT*.

are less sensitive than cost outcomes to the combined (interactive) influence of tariff regime and comfort modelling.

5.7. Summary of section 5

Overall, the DOE/ANOVA confirms three statistically supported findings. First, TCL selection is the primary driver of IT outcomes and materially affects cost. Second, PoCCV operates mainly as a reliability lever, significantly shaping comfort-related outcomes (IT) and influencing operational conservatism under uncertainty. Third, while dynamic tariffs reduce operating costs, their economic value depends on building scale and comfort metric, as evidenced by multiple significant interaction terms in the cost model. These results provide the statistical basis for the discussion of operational implications and configuration guidance in the subsequent section.

6. Discussion

This paper investigated how a home energy management setting can jointly (i) reduce operating cost and (ii) preserve thermal comfort when an air-source HP is scheduled under time-varying electricity prices and uncertain photovoltaic (PV) generation. The results (Section 5) provide three discussion-level insights that are directly relevant to current debates on electrified heating flexibility and household-centred demand response (DR) design.

6.1. Interpreting the cost–comfort trade-off under heat-pump-driven flexibility

The results confirm that residential heat-pump operation provides measurable short-term flexibility, but that flexibility is constrained by (a) building thermal inertia and (b) comfort requirements that are inherently multi-dimensional rather than purely temperature-based. Empirical evidence from Great Britain shows that aggregated domestic HP loads exhibit pronounced morning and evening peaks and can materially contribute to system peak demand, motivating the value of deliberate scheduling approaches that shift load away from critical periods [36]. Likewise, field-trial evidence indicates that "smart" control of hybrid HPs can deliver demand shifting and cost benefits when operation is coordinated with price signals and system conditions [46]. These findings support the paper's premise that cost-minimising schedules must be assessed jointly with comfort impacts, rather than treated as a purely economic optimisation exercise.

In this context, the observed improvements when moving from an IT-only comfort proxy to a PMV-based comfort representation are theoretically consistent with the broader HVAC control literature: PMV-based control captures how occupants experience comfort as a function of temperature plus other determinants (e.g., air velocity, humidity, radiant temperature), which allows control actions to be aligned with *perceived* comfort rather than only air temperature [20]. Therefore, the PMV-driven results should be interpreted not merely as "better comfort modelling", but as enabling a more *actionable* operating space for HP control—i.e., permitting load shifting while keeping the comfort constraint meaningful and physiologically grounded [20].

6.2. Why the DR-CCP + ANOVA combination is methodologically consequential

A central methodological implication is that DR-CCP are a defensible compromise between (i) deterministic schedules that can be brittle under forecast errors and (ii) stochastic formulations that rely on strong distributional assumptions that are difficult to justify with limited local PV data. DR-CCP is explicitly designed to protect constraint satisfaction *across* a family of plausible distributions (rather than one assumed distribution), which is particularly relevant for PV uncertainty where tail behaviour and temporal structure can vary significantly across sites and seasons [50,53]. Recent applications in energy-system planning similarly adopt DR chance constraints to improve out-of-sample robustness without requiring a precise parametric error model, highlighting the practical relevance of this modelling choice for uncertainty-aware energy decision-making [52]. An important implication of this formulation is that the resulting schedules remain feasible across a range of plausible uncertainty distributions rather than relying on a single assumed probability model, which enhances the reliability of comfort-aware operation in renewable-integrated residential energy systems.

ANOVA then adds a complementary layer of insight: it transforms "model outputs" into interpretable evidence about which design factors (and interactions) drive the primary performance outcomes (cost, PMV, power/energy metrics). This is important because DR-oriented formulations can be perceived as technically rigorous but difficult to explain to practitioners; ANOVA helps bridge that gap by identifying dominant drivers and interaction effects in a statistically disciplined way, supported by residual diagnostics that validate model adequacy under the experimental design assumptions [41]. Taken together, DR-CCP improves out-of-sample feasibility under distributional ambiguity, while ANOVA improves interpretability by quantifying main and interaction effects across deployment contexts.

6.3. Practical implications for household DR, aggregators, and tariff design

From a household DR perspective, the results reinforce that operational strategies that merely "avoid peaks" can be insufficient or even counterproductive if they ignore the physics and comfort mechanisms of HPs and buildings. Practical DR implementations for HPs often rely on simple interventions (e.g., setpoint reductions, flow temperature adjustments, compressor blocking), and these choices differ substantially in their comfort and rebound effects [14]. The present findings support the argument that a unified optimisation-and-analysis approach can help select *which* control levers to use and *when*, while quantifying cost and comfort consequences transparently.

From a system perspective, the case is aligned with evidence that smart HP operation can provide cost-effective flexibility and demand shifting when coordinated with price signals [46], and with the broader motivation that aggregated HP load profiles can significantly influence peak demand if left unmanaged [36]. Accordingly, the study's results can be interpreted as supporting a design principle for flexibility programmes: incentives and control schemes should recognise comfort as a first-class constraint and should adopt uncertainty-aware scheduling logic if PV/self-generation is an intended flexibility source [50,52,53].

6.4. Limitations and implications for future modelling

Two limitations should be emphasised when interpreting the generalisability of the findings. First, PMV, while a rigorous comfort index, still depends on assumptions and measurements (e.g., clothing level and metabolic rate) that may vary across households; this motivates future work on occupant-centric or adaptive comfort representations, or robust comfort constraints that explicitly capture behavioural variability [20]. Second, while DR-CCP improves protection against distributional misspecification, its performance depends on how the ambiguity set is constructed and calibrated; future work should test alternative ambiguity constructions and validate robustness using larger multi-season datasets, consistent with the distributionally robust optimisation literature [50,53]. These modelling simplifications are consistent with common practice in building-energy optimisation studies where real-time measurements of all PMV variables are not available. Nevertheless, future research could integrate adaptive comfort models or occupant-specific behavioural data to further refine comfort representation.

Also, although the case study combines validated stochastic demand modelling with historical PV and electricity price datasets, future work

may further strengthen empirical validation by applying the proposed framework to measured building-level datasets from real residential installations.

7. Conclusion

This paper developed a DR-CCP framework for day-ahead scheduling of a PV-assisted HP system under uncertain renewable generation and time-varying electricity prices. Unlike deterministic or scenario-based stochastic scheduling approaches, the proposed DR-CCP formulation explicitly accounts for distributional ambiguity in renewable forecast errors, providing a reliability-oriented framework for comfort-aware HP operation under uncertain conditions. The framework was designed to minimise operating cost while controlling the probability of comfort violations and maintaining operational efficiency. A full-factorial DOE and ANOVA were used to quantify the main and interaction effects of building scale, tariff type, PoCCV, and comfort formulation (IT-based versus PMV-based) on IT, coefficient of performance (COP), and operating cost.

The empirical results show that comfort representation is a primary determinant of performance: PMV-based constraints materially change the feasible operating region and reduce costs relative to temperature-only bounds, while tariff structure also strongly affects cost outcomes. Importantly, the cost ANOVA identifies significant interaction effects among building scale, tariff type, and comfort formulation, implying that tariff-driven savings and comfort-modelling benefits are context-dependent rather than uniform across deployment settings. PoCCV primarily acts as a reliability lever, with stricter PoCCV settings increasing cost due to more conservative schedules that hedge uncertainty.

Practical implications and future research directions are discussed in Section 6. In summary, the findings support treating comfort as a first-class constraint in heat-pump-driven flexibility programmes and motivate further validation across broader datasets and alternative robustness constructions.

The proposed framework provides a decision-support tool for residential energy management under uncertainty, demonstrating how distributionally robust optimisation can support reliable HP scheduling in renewable-integrated residential energy systems.

Overall, the results demonstrate that integrating distributionally robust optimisation with comfort-aware scheduling provides a practical and reliable decision-support framework for managing residential HP flexibility under renewable uncertainty and dynamic electricity pricing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data used in this study are available from: https://data.london.gov.uk/download/2nlqm/81fb6b31-f6b2-4e12-b054-090319faec7b/PV%20Data.zip. The remaining data supporting the findings of this study are provided within the article.

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