Identifying Dominant Factors of Domestic Thermal Demand Response Using Local Sensitivity Analysis of Multiple Flexibility Metrics

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ABSTRACT

Thermal demand response (TDR) can provide energy flexibility, by dynamically controlling a dwelling's heating, ventilation and air conditioning (HVAC) system or thermal storage system. Buildings, their energy systems and controls are hugely complex, which makes it challenging to identify which factors are most important in leveraging a dwelling's TDR potential.

In this study, a population of 25 detached dwellings are simulated using Modelica's Spawn of EnergyPlus. Dynamic changes to indoor air temperature setpoints, using rule-based control, were used to adjust the demand of an air-source heat pump – thereby delivering a TDR. A local sensitivity analysis was used to examine a range of factors that may impact a dwelling's TDR potential. To explore the TDR potential, 12 parameters were varied by ±1% from a base case and quantified using the flexibility factor (FF) and flexibility performance indicator (FPI). The study also compared the effects of price-driven and emissions-driven building-grid interaction signals on TDR.

The results show that *initial setpoint temperature* is the most dominant factor, where a 1% increase (0.2°C) increased the FPI by up to 8.4% and the load shifting capacity (FF) by 2.3%. The *duration of the TDR period* (FPI = -4.0%, FF = 0.5%) and *infiltration rate* (FPI = -1.4%, FF=-0.2%) were also dominant factors but had an overall destructive effect. Additionally, the FPI, which describes system operation, is more sensitive to ±1% variations than the FF, which describes whole-system performance – but over a wider range of ±5% variations, the FF exhibits a more significant and consistent change than the FPI, suggesting that further work is required.

Keywords: Thermal demand response, Building energy modelling, Local sensitivity analysis, Energy flexibility.

INTRODUCTION

Background

The UK government emphasises energy flexibility as a key enabler to achieve net-zero goals by balancing demand and supply of intermittent renewable energy. However, assessing the built environment's energy flexibility potential is challenging due to the complexity and variability amongst the building stock. Energy flexibility often stems from the concept of demand-side management, first popularised in 1985 by Clark W. Gellings [1] where it was argued that energy flexibility is a key tool to support grid stability through different services, as per Figure 1. Nearly 40 years on and energy flexibility has become critical in its ability to help enhance grid stability whilst integrating intermittent renewable energy sources, by reducing peak loads and active load shifting.

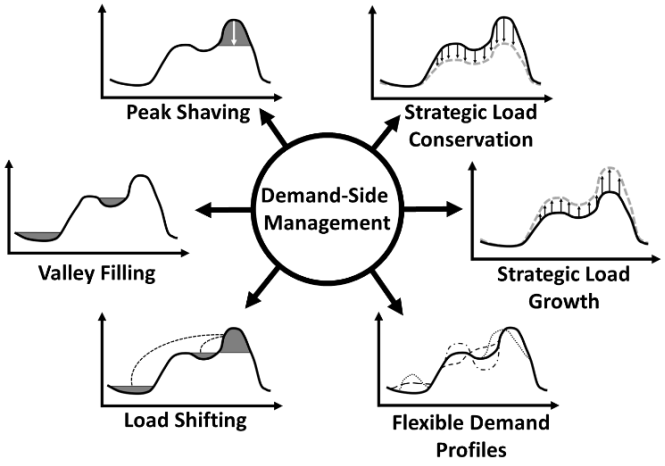

Figure 1: An adapted image from [1] illustrating how different demand-side management services can impact load profiles.

Thermal demand response (TDR) is a key strategy in achieving energy flexibility, where its significance lies in its potential to shift or reduce energy use when needed.

In this study, we define a building's TDR potential as "*a measure of its ability to respond to changes which may impact the building's regular energy demands by dynamically controlling the power demands of the heating, cooling or thermal storage systems, without compromising comfort*."

Identifying the dominant factors that influence a building's TDR potential is critical for accurate assessment at the single- and multi-building scale but is also extremely challenging; particularly for smaller buildings and dwellings, where the impacts of different factors could have significant changes to energy use and TDR potential when aggregated to the urban scale.

A comprehensive review paper by Li *et al.* (2021) [2] highlighted key variables which can significantly impact the TDR potential of a domestic dwelling. These include (but are not limited to) thermal mass, energy storage, responsive technology controls and user interaction. As an extrapolation of these variables, four themes can be used to categorise such variables when quantifying TDR of buildings, as shown in *Figure 2*.

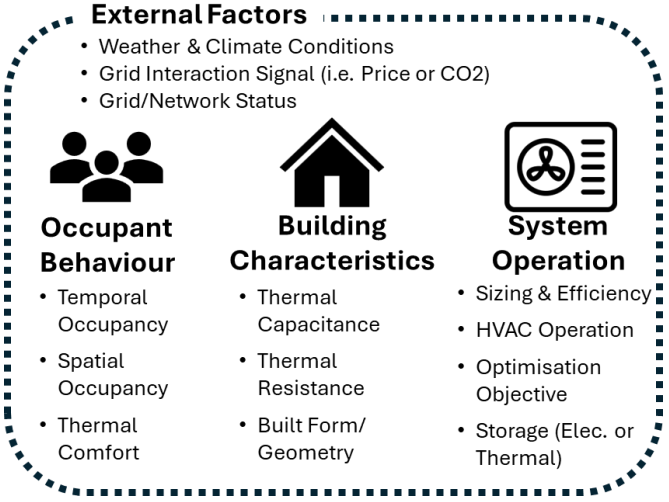

Figure 2: Details of three key areas which can impact a building's TDR potential within the boundary conditions (external factors), to quantify the delivered TDR.

Uses of Sensitivity Analysis in Energy Flexibility

Due to the complexity of modern building energy systems, the use of sensitivity analysis (SA) has been widely used in building energy research. Halls *et al.* (2021) [3] evaluated the impact of varying a building's energy efficiency on the annual energy demand, they considered each of the building characteristics (fabric and geometry), system operation (heating efficiency and responsiveness), and the occupant behaviour (occupancy, setpoint settings and heating schedule). They found that with more energy efficient dwellings, the sensitivity of building characteristics diminishes whilst system operation and occupant behaviour become more important. This finding was corroborated by other studies focussed on the application of TDR, such as Le Dréau *et al.* (2020) [4], where they explored the sensitivity of occupant's behaviour on TDR, considering presence, heating behaviour and appliance use. Martinez *et al.* (2022) [5] used local SA (Morris Method) to identify the dominant factors specific to a domestic district, where the duration of the TDR event and change in temperature were significantly more dominant than the next most influential factors (heat pump performance, occupant probability of changings set points, air change rates and internal thermal mass).

The studies noted here have been successful in their identification of dominant factors when only considering one metric. But as several other studies have commented [2, 6, 7] energy flexibility, and by extension TDR, is multifaceted and benefits from using multiple metrics, rather than just one, as this can inform a more comprehensive analysis about the building-energy system heuristics and the wider impacts of providing TDR. For example, Johra *et al.* (2019) [6] used SA to compare different aspects of the building's characteristics across different flexibility performance indicators presented by Junker *et al.* (2019) [7]. This resulted in a much more complete understanding of which elements of the TDR service were impacted by the changed parameter in the SA.

Therefore, the objective of this study is to identify the dominant factors of TDR by comprehensively exploring their simultaneous impact on multiple flexibility metrics. The originality of this work lies in the use of multiple inputs and outputs to a SA focussed on dwelling's TDR potential. As such, this study focuses on a segment of the building stock by exploring the variance around a base-case dwelling and occupant profile in a geographic region. This work is one step towards informing the efficacy of targeted policies to enable TDR of dwellings at single- or multi-building scales, by testing the suitability of flexibility metrics and analysis techniques.

METHODOLOGY

Model Development and Verification

A population of 25 models were developed around a base-case using DesignBuilder software and simulated using Modelica's Spawn of EnergyPlus [8]. The model, as detailed later in this section, was verified by comparing typical annual energy demands from a typical detached UK dwelling. A SA was applied to allow the simulation of a population of similar dwellings. The geometry for the base case was drawn from the widely cited report by

Allen and Pinney (1990) [9], A&P hereafter, which details '*Standard dwellings for modelling: details of dimensions, construction and occupancy schedules.*' Although this report is dated, a study by the Building Research Establishment argues that because 83% of the current building stock was built prior to 1990, these details are still relevant today [10].

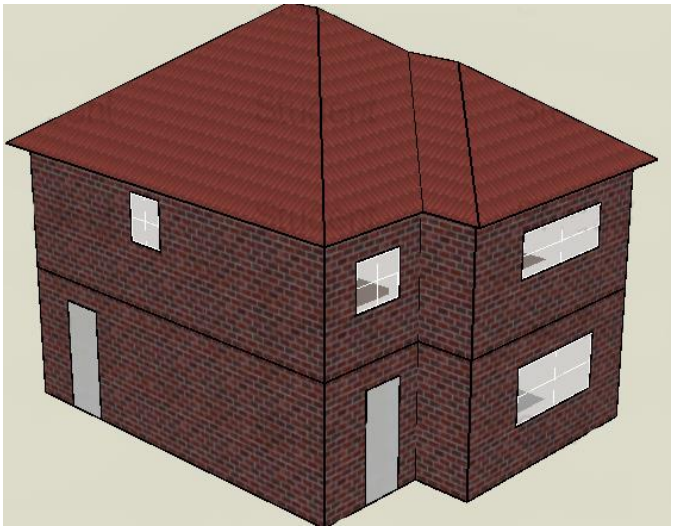

Figure 3: A rendered image of the base case dwelling.

The base case model, as shown in *Figure 3,* is a south facing two-storey detached dwelling assumed to have a ground floor area of approximately 50m^2 and a total floor area of 100m^2. It comprises nine thermal zones representing each room of the dwelling (Table 2). It is assumed that there is no inter-zonal airflow and so only conductive heat transfer is considered between zones. The thermophysical properties of the dwelling can be seen in *Table 1*. The dwelling is situated in central England, Birmingham and a design heat loss calculation was made using -1˚C external temperature.

Envelope Element	Area (m^2)	U-value (W/m^2 K)*	Thermal Capacity (MJ/K)
External Wall	127.35	1.46	38.00
Internal Wall	164.02	1.97**	27.62
Ground Floor	51.53	0.90	9.09
Windows	10.56	4.51	-
Ext. Doors	5.65	3.13	-
Roof	83.43	0.32	2.21

*Table 2: A table of thermophysical properties for the base case model. *U-values as calculated in EnergyPlus. **Internal walls treated as adiabatic for verification.*

The A&P model assumes an active bi-modal heating schedule (i.e. 7-9am and 16-23pm), with a setback temperature of 12˚C. Radiators were sized to 120% of the calculated design heat loss of reach room and have a radiant-to-convective split of 20:80 (%). Casual gains due to lighting, appliances and occupancy assumes a "light occupancy" profile as described by A&P in table 42 of their report – these were used for verification of the model but not in the calculation of the TDR potential. Other design values are detailed in Table 2.

	Infiltration (ACH)	Temperature Setpoint (˚C)	Radiator Sizing (W)
Living	1.0	21	1979.78
Dining	2.0	21	1850.21
Kitchen	2.0	18	1165.81
Hall/Landing	1.5	16	1481.65
Bedroom 1	0.5	18	1201.22
Bedroom 2	0.5	18	903.13
Bedroom 3	0.5	18	578.62
Bathroom	2.0	22	743.36

Table 1: A table of nominal design parameters for the base case model.

It was noted that the archetype as described by A&P is not fully representative of modern-day dwellings. Therefore, three additional changes were made to the A&P model description, with the resultant base case model being checked against typical annual demands to ensure suitability and robustness:

1. Single Setpoint: Every room considered to have the same setpoint of $T_{Int} = 20^{\circ}C$.
2. Daytime Heating: Active heating during the daytime, 7am to 10pm – no minimum setback temperature.
3. Improved Fabric: Improved window U-value ($U_{Win} =$ 2.7 W/m^{2}K), filled cavity ($U_{ExtWall} = 0.465$ W/m^{2}K).

The air-source heat pump (ASHP) model used was the *Carnot_TCon* available in the Modelica Buildings library, using nominal operating conditions of 55˚C and 7˚C for the respective evaporator and condenser temperatures, a coefficient of performance (COP) of 3.23 and a peak thermal output of 13.6 kW$_{th}$. The part-load (PL) efficiency curve used coefficients of $a_1 = 0.75, a_2 = 0.25$.

To verify the base case model, a steady-state heat loss for the envelope, Q, was calculated using Eq.1, and compared against values provided by A&P.

$$Q = \left[\sum (A \cdot U) + \frac{nV}{3}\right](T_{Int} - T_{Ext}) \quad (1)$$

Where, $\sum(A \cdot U)$ is the area weighted construction U-value (W/K); n is the infiltration rate (ACH); V is the volume of the thermal zone (m^3); T_{Int} is the internal air temperature of the zone (˚C) and T_{Ext} is the external air temperature of the environment (˚C). The space heating demand of the base case was verified further using a typical annual space heating demand of 10,440kWh,

considering gas demand of 13,600kWh, 2000kWh for hot water usage and a typical 'combi' boiler efficiency of 90% [11].

Characterising A Thermal Demand Response

A flexibility characterisation often comprises several quantification metrics, all considered equally or in a weighted arrangement. The characterisation method considered in this study uses a combination of two commonly used quantification methods in the form of the flexibility factor (FF) [12] and flexibility performance indicator (FPI) [13] respectively.

The FF quantifies the load-shifting potential of the TDR strategy from an unfavourable to favourable period, as per Eq.2. If 100% of the energy is shifted $FF = 1$ and if 0% is shifted, then $FF = -1$. In this work the FF was used to consider TDR impacts of shifting energy only, however it also has utility to evaluate other variables like cost or carbon emissions.

$$FF_{TDR} = \frac{\int_{Low\ FGIS} Q \cdot dt - \int_{High\ FGIS} Q \cdot dt}{\int_{Low\ FGIS} Q \cdot dt + \int_{High\ FGIS} Q \cdot dt} \quad (2)$$

The FF requires a Building-Grid Interaction (BGI) signal to determine the high (*unfavourable*) and low (*favourable*) periods for the system. In this study, two BGI signals were used – the operational cost of energy, and the operational carbon intensity of the energy. The cost of energy was calculated as the product between the operational energy use from heating and the active price for each half-hour period using the Octopus Energy Agile Tariff electricity price [14]. Similarly, for carbon intensity of energy use, historical electricity carbon intensity data was used from National Grid [15]. To trigger the TDR, the limits of 20 p/kWh and 120 gCO_2/kWh were used for the price-based BGI and emissions-based BGI signals respectively. The periods when the BGI signal was above these values would be 'unfavourable' and, therefore, trigger a TDR by dropping the set-point temperature as per Figure 4.

The FPI (Eq.3) comprises four weighted metrics as per Eqs. 4, 5, 6 & 9.

- The response time (t^*_{res}) is the time (hours) required for the temperature to reach the TDR comfort bound (weighted by $p_1 = 0.6$ and normalised over 24 hours).
- The power capacity ($\dot{P}^*_{res}$) represents the actual electrical power change due to TDR (weighted by $p_2 = 0.2$ and normalised by nominal appliance power, $P_{Nom} = 4.21\ kW$).
- The recovery time (t^*_{rec}) is the time (hours) required for the temperature to get back to the baseline set point (weighted by $p_3 = 0.1$ and normalised over 24 hours).
- System efficiency (η_{DR}) is a measure of the system's ability to reduce energy relative to the base case during the TDR period (weighted by $p_4 = 0.1$ and normalised by the nominal appliance power).

$$FPI = \frac{(p_1 \cdot t^*_{res} + p_2 \cdot \dot{P}^*_{res} - p_3 \cdot t^*_{rec} + p_4 \cdot \eta_{TDR})}{4} \quad (3)$$

$$t^*_{res} = \frac{t_{res}}{24} \quad (4)$$

$$\dot{P}^*_{res} = \frac{\int_0^{t_{res}} (P_{Base} - P_{TDR}) \cdot dt}{t_{res} \cdot P_{Nom}} \quad (5)$$

$$t^*_{rec} = \frac{t_{rec}}{24} \quad (6)$$

$$t_{TDR} = t_{res} + t_{rec} \quad (7)$$

$$E_{TDR} = \int_0^{t_{TDR}} (P_{Base} - P_{TDR}) \cdot dt \quad (8)$$

$$\eta_{TDR} = \begin{cases} \dfrac{E_{TDR}}{\int_0^{t_{TDR}} (P_{Nom}) \cdot dt} \\ 0 \ \ (if \ \ E_{TDR} < 0) \end{cases} \quad (9)$$

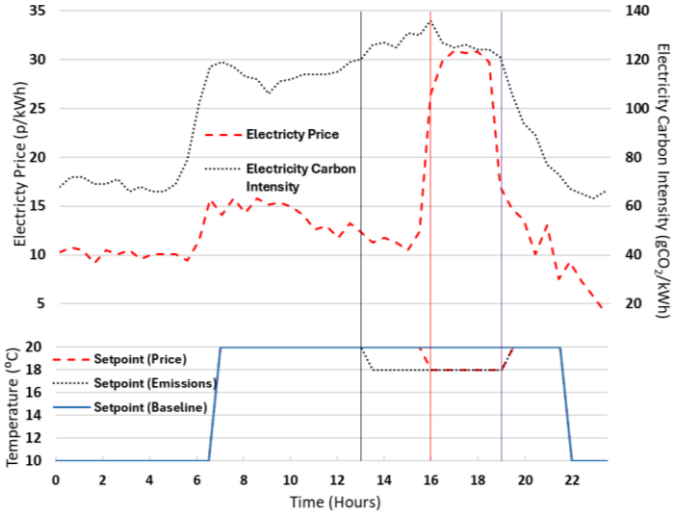

Figure 4: A timeseries plot of the electricity price and carbon intensity for the 1st of February 2023. It illustrates the variation of the setpoint due to the delivery of a TDR service from the relevant BGI signal over the day, with trigger points indicated by vertical lines.

Local Sensitivity Analysis

A local sensitivity analysis was performed by calculating the effects on model outputs from small changes around a nominal (base case) parameter value. The change was made one parameter at a time to quantify the change in outputs due to the change in input for that variable. The

output of which is a *sensitivity coefficient* equivalent to the change in outputs due to the change in inputs. The *sensitivity coefficient* can be calculated according to a *finite-difference approximation* around a central point, as per Eq.10 for *n* output variables and *m* inputs.

$$\frac{\partial y_i}{\partial x_i} \approx \frac{y_i(k_j + \Delta k_j) - y_i(k_j - \Delta k_j)}{2\Delta k_j} \quad (10)$$

$$S_{i,j} = \frac{k_j}{y_i}\frac{\partial y_i}{\partial x_i} \quad (11)$$

Where, ${}^{\partial y_i}/_{\partial x_i}$ is the sensitivity coefficient, y_i is the i'th output variable from $i = 1, \dots, i = n$; k_j is the j'th input parameter from $j = 1, \dots, j = m$; Δk_j is the increment in k_j which is considered; $y_i(k_j + \Delta k_j)$ is the value of y_i when k_j is *increased* by a small increment of Δk_j and $y_i(k_j - \Delta k_j)$ is the value of y_i when k_j is *decreased* by a small increment of Δk_j. Eq.10 can be transformed by normalising the sensitivity coefficient, as per Eq.11. The interpretation of this output is a relative percentage change to the input is produced – this allows comparisons to be made between parameters of different units. The choice of small 1% changes limit the effects of non-linearity, which can occur in a dwelling's interaction with external factors [5]. This SA technique was chosen due to its success in previous building energy simulation studies [3, 16] and ease of interpretation across varying and disconnected inputs.

Category	Input Variable	Initial Value	1% Change
Building Properties	Envelope Heat Capacity (J/K)*	877.55	±8.7755
	Envelope U-value (W/m²K) **	0.987	±0.00987
	Window U-value (W/m²K)	2.716	±0.02716
	Infiltration Rate (ACH)***	1.394	±0.01394
Occupant Behaviour	Setpoint Temperature (°C)	20	±0.2
	Heating Period Length (Hours)	15	±0.15
	TDR Setpoint Change (°C)	2	±0.02
System Operation	Heat Emitter Power (W)	3253	±32.53
	ASHP Efficiency (COP)	3.23	±0.0323
	Mass of Radiators (kg)	229	±2.29
	Flow Temperature (°C)	55	0.55
DR Dispatch	Length of TDR (Price [Emissions], Hours)	3 [6.5]	±0.03 [±0.065]

*Table 3: A table of prominent factors for leveraging a building's TDR which have been identified through the literature review. *Envelope heat capacity of is the total mass-weighted specific heat capacity of the materials used in the walls (external and internal) and ground floor. **Envelope U-value calculated as the area-weighted U-value of external wall, ground floor and roof. ***Infiltration is the volume-weighted ACH for each thermal zone.*

Table 3 illustrates a series of 12 prominent factors for TDR identified by literature that were used in the SA. Each factor was varied twice (i.e. ±1%) to provide a population of 25 dwellings (inc. the base case) considered around the central base case (i.e. $m = 24$). For the most significant factor, a linearity test was used to determine the strength and nature of the relationship between inputs and outputs across the metrics. The heat capacity and U-values were changed by editing the specific material's heat capacity and conductivity, respectively, in EnergyPlus. All other modifications were made by changing control values in Modelica. As described earlier, the flexibility metrics considered comprise the FPI (5 metrics) and the FF – therefore $n = 6$. For simplicity, a representative UK winter (heating season) day of the 1st February was used to run the SA simulations for the flexibility metrics.

RESULTS

Model Verification

The verification results of the base-case show a very good alignment between the theoretically calculated thermal losses at the building element level, with an overall difference in thermal loss of 4.7%. The most significant difference, in absolute measures, was the external wall which was overestimated by 359.3 W (10.2% above the theoretical calculation). Further comparison of the developed models to the annual space heating demand and results of other studies using this detailed archetype [17] exhibit good alignment within 5%.

Baseline TDR Characterisation

Applying both price- and emissions-driven TDR to the base case model yielded the results as per Table 4. The interpretation is such that when requested, the dwelling was able to reduce its electrical power demand for heating by 518W over a period of 42 minutes for the price-driven TDR, and 785W for 76 Mins for the emission driven TDR. The recovery period (time taken to raise the temperature back to a pre-TDR level) was 7 and 6 minutes with the net impact on energy of providing the TDR service being a reduction of 0.266kWh$_e$ and 0.301 kWh$_e$ for each scenario respectively. The flexibility factor considers the entire *unfavourable* period and suggests that 90.1% and 76.4% of energy use was during the *favourable* period for each scenario, showing successful implementation of the TDR strategy. The differences between the two scenarios can largely be attributed to the weather conditions when the TDR was required

(daytime for emissions-driven and early evening for price-based). The length of the TDR also has a significant impact on the FF due to the proportion of energy used between the *favourable* and *unfavourable* periods.

Metric	Physical Result	TDR Result	Physical Result	TDR Result
Response Time	42 Mins	0.034	76 Mins	0.053
Response Power	0.518 kW_e	0.165	0.785 kW_e	0.147
Recovery Time	7 Mins	0.005	6 Mins	0.004
TDR Efficiency	0.263 kWh_e	0.094	0.301 kWh_e	0.101
FPI	-	0.063	-	0.072
FF	90.1%	90.1	76.4%	76.4

Table 4: The base-case dwelling TDR characteristics from the FPI metrics and FF in physical terms and the resultant metric value. The left- and right-shaded columns are for the price- and emissions-driven TDR results respectively.

Sensitivity Analysis of Flexibility Metrics

The results of the sensitivity analysis for the price-driven and emissions driven TDR are shown in Figure 5. From this figure, it is clear that the initial setpoint temperature has the most significant impact on the FF and FPI. A 1% increase in initial setpoint temperature (0.2°C) reduced the FPI score of the dwelling by up to 3.8% and decreased the load shifting capacity using the FF by up to 0.98%; as the difference in setpoints remained the same, the rate of heat loss was faster at a higher temperature. Several other factors, notably the heating period length and setpoint change due to TDR, had notable impacts on one of the metrics (i.e. had an average >1% change in output).

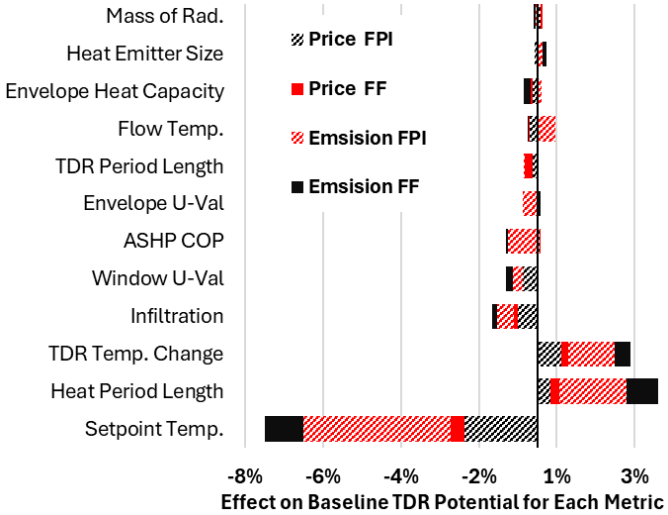

Figure 5: The cumulative sensitivity of 1% changes for different factors, on the FPI (striped) and FF (full) metrics in the price-driven (red) and emissions-driven (black) TDR scenarios.

It was inconclusive, for some factors, if they have a certain positive or negative impact – as can be seen for the flow temperature and envelope heat capacity parameters, where the impact on metrics varied depending on the BGI signal used. The comparison between FF and FPI metrics demonstrates, in this study, that operationally-focussed metrics like the FPI are more sensitive to variation than external-impact metrics like the FF. As shown in Figure 6, the response time is the dominant metric for both BGI signal used. Given the heavy weighting towards this 'grid-relevant' metric, the FPI may be too biased towards network stakeholders rather than occupants as the impacts on the occupants are much harder to evaluate using this metric.

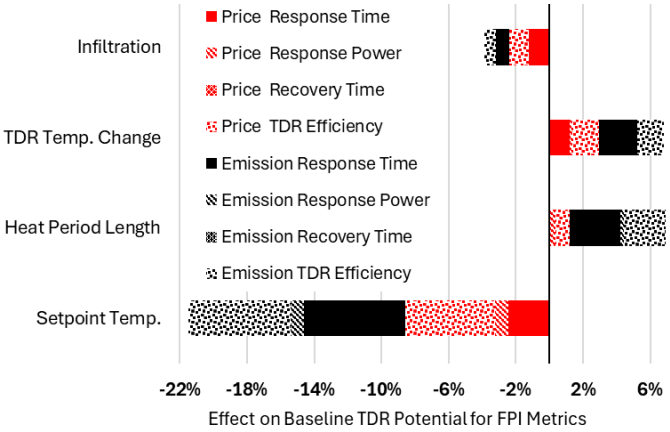

Figure 6: The cumulative sensitivity of 1% parameter changes for the FPI metrics, across the price-driven (red) and emissions-driven (black) TDR scenarios.

Linearity Effects for Most Dominant Factor

As is clear from Figure 6, the setpoint temperature is the most dominant factor identified in this study of minor perturbations, therefore, to explore the effects of the variations over a wider range of inputs a linearity test was performed, and the results shown in Figure 7.

The figure shows that over ±5% deviation, the metrics considered do not exhibit a perfectly linear relationship, particularly the FPI which is less linear (R^2=0.911) compared to the FF (R^2=0.986).

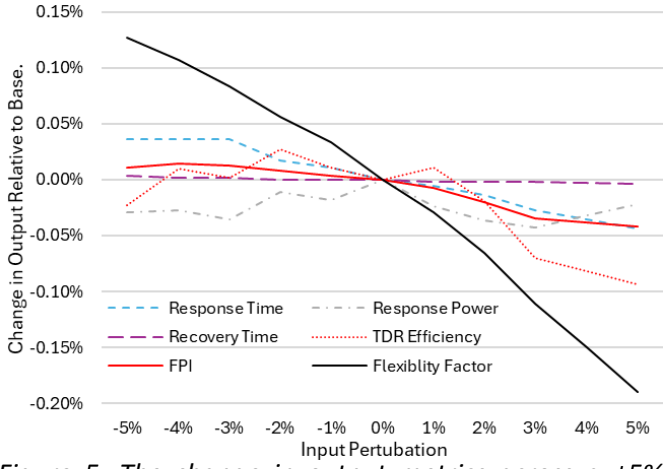

Figure 5: The change in output metrics across a ±5% perturbation of the most dominant factor in this study.

DISCUSSION

Applicability of TDR Metrics to Evaluate Performance

The interpretation of different TDR metrics in real-world scenarios was considered by using both the FPI and FF metrics. Overall, the FPI metrics were impacted more-so than the FF, suggesting that the accuracy of operationally-focussed metrics for dwelling TDR potential may be severely affected by the uncertainty due to dominant factors. Further, the weighting of different metrics comprising the FPI can also have an influence on the sensitivity, as factors which do not impact the response time or power capacity as much have less impact on the FPI calculation. This queries the suitability of this particular FPI weighting.

An important part of delivering a TDR is how the control strategy reacts to the active BGI signal. The use of different BGI signal does not have an inherent impact on the triggering of a TDR. Rather, the differences lie in the timing and length of the TDR period and, therefore, the proportion of time a dwelling is operating in a *favourable* or *unfavourable* scenario. In a world where the dynamics of price and emissions are discussed at national and international levels, the use of these BGI signals to trigger a TDR should be carefully considered.

Implications for Policy and Design of Dwellings at Scale

The factors explored in this work have direct impact to the design of buildings in the aggregate, their energy systems and how they are used by occupants. It is inconclusive how effective improving a dwelling's envelope heat capacity can be at such a marginal level (1%), but policies which improve airtightness and reduce window U-values by such levels can improve a dwelling's TDR potential, this is particularly the case for zones/dwellings with high glazed ratios.

The most significant impact on TDR can be made by engaging occupants, such that those who have longer heating periods or higher setpoints can exercise their improved TDR potential and higher energy saving potential. Counterintuitively, occupants who already adopt energy saving measures (shorter heating periods and lower setpoints) could have a lower TDR potential.

Dominant Factors' Influence on Uncertainty at Scale

Although this work has quantitatively identified some dominant factors of TDR, it is noted that these factors are also major sources of uncertainty. For example, there can be a significant range in temperature setpoints and infiltration rates (due to window/door opening behaviours or build quality) across urban districts and regions. Therefore, accurate identification and quantification of these factors is the first step towards reducing the uncertainty of TDR, or energy flexibility more generally, at muti-building scales. The quantification and understanding of uncertainty at multi-building scales is critical for service providers, aggregators and network operators to accurately determine the TDR/energy flexibility potential of dwellings for business feasibility.

Limitations of this Study

The applicability of the findings from this study to other case-study buildings is limited, because factors such as building characteristics and occupant behaviour do not naturally change by 1% at a time. Further work will be undertaken to fully realise the impacts of this methodology by exploring more intuitive step changes in these factors on multiple flexibility metrics.

This study omits the impact of hot water demand on load-shifting, which could significantly limit flexibility, especially when hot water takes priority over heating. Future work should incorporate hot water profiles to assess this impact. Additionally, the analysis is limited to a single day, restricting responses from dynamic responses influenced by climate, occupant behaviour, and BGI signals. Extending the simulation to cover longer periods would improve confidence in the study's findings by including seasonal variations to provide more robust and generalisable results.

CONCLUSIONS

The identification of the dominant factors influencing domestic Thermal Demand Response (TDR) in dwellings was achieved successfully. Through independent simulation of 25 dwellings via a sensitivity analysis and employing peak shaving TDR strategies (by lowering temperature setpoints), the research highlighted setpoint temperature, length of TDR, and infiltration rates as the primary determinants impacting TDR. The novel approach of utilising multiple flexibility metrics has demonstrated the varying sensitivities of operationally-focussed (FPI) and externally-focussed (FF) metrics, where operationally-focussed metrics exhibit greater responsiveness to variations compared to externally-focussed, albeit with limitations in their quantification over such a narrow variation.

The results have identified the *initial setpoint temperature* as the most dominant factor, as a 1% (0.2^{o}C) increase caused a reduction of 3.80% and 0.98% of the FPI and load shifting capacity (FF) respectively. The *duration of the heating period* ($FPI_{Avg.}$= 1.03%, $FF_{Avg.}$= 0.53%) and *TDR setpoint change* (FPI_{Avg}= 0.90%, FF_{Avg}= -0.30%) were also identified as dominant factors – all of

which are occupant driven. The findings also highlight the importance of refining TDR metrics to better evaluate performance for different stakeholders and the broader implications for policy and design of dwellings at scale. The identification of dominant factors also aids in understanding and quantifying the uncertainty of TDR across multi-building populations. This research provides a critical contribution towards enhancing the efficacy of TDR strategies, offering valuable insights for policymakers and designers aiming to optimise operational efficiency in dwellings.

The future of this work should focus on further validation of combining metrics to better inform the impacts of TDR. Additionally, exploring more natural variations in the building stock to quantify the uncertainty that exists within the stock. Coupling this work on sensitivity analysis with future work on uncertainty analysis will provide a more robust quantification of the built environment's TDR potential.

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