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Research paper

Quantifying the value of building demand response: Introducing a cross-sectoral model framework to optimize demand response scheduling

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ABSTRACT

Co-optimization of demand-side electrification and supply-side variable renewable energy integration in electricity systems can lead to dramatically reduced emissions due to synergies between the two sectors. However, few models exist that represent both sectors in sufficient operational detail. To bridge this gap, this paper proposes a novel framework for transferring information from a building stock model to an electricity system model. First, demand response (DR) events are simulated within a model of building stock energy use. Then, the energy characteristics of these events are used to inform a series of constraints within the electricity system model. At the same time, hourly electricity use predictions from the building stock are also incorporated into the total demand met by the electricity system. This allows the electricity system model to determine the grid-optimal times for the building stock to enact DR. To demonstrate the utility of this framework, a case study into the effects of building efficiency increases, DR, and variable renewable capacity expansion in the city of Regina, Saskatchewan is performed, and various ways to reduce the costs and emissions associated with electricity use in Regina are compared.

1. Introduction

Buildings are responsible for roughly 40% of greenhouse gas (GHG) emissions globally (United States Department of Energy, 2015). In Canada, two-thirds of residential energy is used for heating, and natural gas (NG) is the primary heating fuel for over half of households (Natural Resources Canada, 2020, 2022; Statistics Canada, 2022). Increasing building efficiency and switching to electric heating therefore represents a large potential for the reduction of greenhouse gas emissions, especially when that electricity is powered by renewable generation. Building electrification and efficiency upgrades also provide an opportunity to co-optimize the operation of electricity and building systems.

Due to rapidly declining costs combined with the Paris Agreement (United Nations, 2023) and other global efforts to reduce carbon emissions, variable renewable energy (VRE) technologies such as wind and solar have been gaining prominence in markets and contributing increasingly more electricity to grids worldwide. However, the reliance of these technologies on weather conditions complicates supply and demand balancing, particularly on grids that have little storage capacity and inflexible generation needs (Kroposki, 2017; ESMAP Energy Sector Management Assistance Program, 2023). Electrification of building heating and cooling systems provides an opportunity to reduce the severity of these problems through demand response (DR) strategies, through which electricity demand changes in real time to accommodate the conditions of power availability. Examples of DR include pre-heating or cooling based on predicted mismatches between energy supply and demand, and/or relaxing the internal temperature setpoints of buildings at times when electricity demand is high and supply is low (Razmara et al., 2017). Such actions take advantage of buildings' thermal mass to change the timing of building energy load and, if implemented correctly, can have only a moderate impact on the comfort of building occupants.

DR is an area of interest for both the electricity system and the building sector. As a result, modelling work in both sectors has come up with ways to represent and optimize DR. On the building side, Luo et al. (2020) and Anvari-Moghaddam et al. (2015) both propose algorithms to schedule the timing of home appliance use (including heating and cooling) by accounting for time-sensitive electricity prices and minimizing the cost associated with required device operation. Similarly, Li

Abbreviations: ASHRAE, American Society of Heating, Refrigeration, and Air Conditioning Engineers; BC, British Columbia; $CAD, Canadian dollars; GHG, greenhouse gas; DR, demand response; GSHP, ground source heat pump; $K, thousand dollars; kg CO2e, carbon dioxide equivalent kilograms; KW, kilowatt; m, meters; MW, megawatt; MWh, megawatt-hour; NG, natural gas; tCO2e, carbon dioxide equivalent tonnes; VRE, variable renewable energy.

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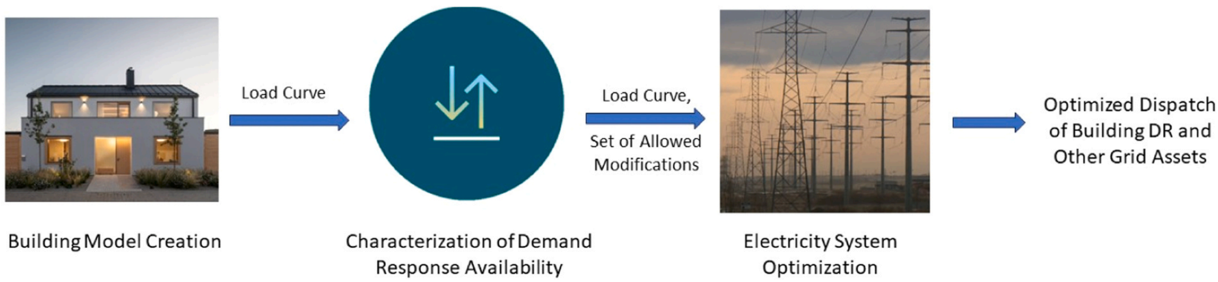

Fig. 1. Model workflow for this study. Images represent the three major steps of the model linkage, while arrows are labelled with inputs/outputs for each step.

et al. (2022) optimize the operation of building thermal and appliance loads alongside building-integrated photovoltaics and battery storage while also considering the price of electricity drawn from the grid. Other papers such as Papaefthymiou et al. (2012) and Magni et al. (2020) model minimum and maximum building energy use needed to maintain reasonably comfortable thermal conditions, and then schedule electric grid operation while taking those building energy requirements into account. There are also techniques such as non-intrusive load decomposition (Zhao et al., 2019; Salani et al., 2020; Lin et al., 2023; Ou et al., 2023), in which flexible components of building load are identified and scheduled accordingly.

Similarly, on the electricity side, Morales-España et al. (2022) classify different types of DR and propose a linear formulation for incorporating DR strategies into a large-scale energy system model. Their formulation includes the curtailment of a set amount of energy, subject to constraints on the frequency and length of curtailment, as well as the shifting of a variable amount of energy, subject to constraints requiring a minimum and maximum shiftable energy and the timely recovery of shifted load. Kachirayil et al. (2022) review local energy system models and similarly note that DR strategies are typically modelled by identifying specific loads which are able to either be curtailed in emergency situations, or shifted in time within a specific interval. Wang et al. (2021) and McPherson and Stoll (2020) both apply detailed constraints representing the operation of different demand-response sensitive devices; Wang et al. optimize the timing of appliance energy use within an acceptable time frame, while McPherson and Stoll use constraints to ensure that shifted power is recovered within a certain time interval and that shifts are sufficiently spaced in time.

However, despite well-developed models on both the supply and demand side, there is limited work that addresses BOTH sectors in operational detail. On the building side, the models described above all have various shortcomings. Rather than directly co-optimizing building device operation alongside grid asset dispatch, Luo et al. (2020), Anvari-Moghaddam et al. (2015), and Li et al. (2022) all use price information as a proxy for the necessity of DR strategies. Likewise, (Papaefthymiou et al. (2012) and Magni et al. (2020) assume that building thermodynamic load is always available for utility control, which may not be the case for residential buildings. Meanwhile, Zhao et al. (2019), Salani et al. (2020), Lin et al. (2023), and Ou et al. (2023) are more focused on techniques for analyzing load, rather than coming up with ways for the grid to use the determined flexibility. On the electricity side, the modeling paradigms presented in Morales-España et al. (2022) and Kachirayil et al. (2022) still require a demand-side model to determine flexible load, and fail to incorporate that load flexibility may dynamically change based on changing energy requirements throughout the day and year. Similarly, Wang et al. (2021) and McPherson and Stoll (2020) both rely on fixed and static parameterizations to represent building system demands and constraints, which also fails to capture the dynamic nature of building energy demand.

The existence of shortcomings in regards to the comprehensiveness and scope of supply- and demand-side focused models is also supported by the review literature. A review of Canadian models relating to decarbonization found that although each sector has a well-developed suite of models, crossover between different sectors is essentially non-existent (McPherson et al., 2023). Regarding buildings, a review by Pallonetto et al. (2020) found that the field lacks a common metric for flexibility that can be used across different technologies and building types; this makes it difficult to extract values that can be used to populate the flexibility constraints of electricity system models. A review by Li et al. (2021) similarly noted that building-side flexibility studies often fail to discuss how flexibility could be incorporated into existing electricity market activities, making it difficult to understand how to actually implement DR strategies. Regarding the electricity system, Chang et al. (2021) reviewed 54 different electricity system modeling tools and found that only half of these included a representation of building heating demand; even when this demand was modelled, it was almost always used as an estimated input rather than a direct tie-in to a building model, making the reviewed electricity system models unable to effectively compare the impacts of different DR strategies. A review by Savvidis et al. (2019) likewise identified demand-side changes and demand-side grid flexibility as two questions that energy system models were not well-equipped to address. Finally, the focus of these review papers on either one sector or the other, but not both, further supports the lack of integrated modeling work that spans both electricity supply AND electricity demand in operational detail.

To overcome the tendency towards sector-specific modeling which is seen in the literature, this paper proposes a novel model linkage between an operational electricity system model and an operational building stock model. This is achieved via two connection points: first, the electricity load which is output from the building stock model is used as an input for the electricity system model. Second, demand flexibility is characterized as the energy available for distinct DR events at different times of the day and year. These energy values are then used to inform constraints within the electricity system model, allowing the timing of the building DR events to be optimized from the perspective of the electricity system. To demonstrate its utility, this framework is developed for and applied to a case study of Regina, Saskatchewan, a city which is notable in Canada for its high renewable potential (Seatle et al., 2021). The case study sheds light on the potential value and operational specifics of DR in Regina by comparing three levels of energy shifting (based on temporary thermostat setpoint degree change and the frequency and duration of such events) across two building stock and grid compositions (differentiated by envelope upgrades, the installation of highly efficient ground source heat pumps, and the expansion of VRE generation capacity).

The rest of this paper is organized as follows. First, an overview of our linkage methodology is provided. Next, since the specific details of each model are dependent on the characteristics of the real-world systems described by that model, the details of our case study of Regina are presented. The model linkage framework for the case study is then constructed in detail and validated. Finally, the results are presented; we show that changes in the timing of building energy use due to building efficiency increases can cause significant changes in the timing and impact of DR events, that shifting large amounts of energy at once is advantageous, and that start-up costs as well as costs per megawatt-hour (MWh) are important in determining how the capacity factors of different energy sources are impacted by the implementation of DR.

2. Methods

To optimize the scheduling of building DR events from the perspective of the electricity system, model linkage between a building stock model and an electricity system optimization model is accomplished via three major steps (Fig. 1). First, during *building model creation*, a detailed model of the building stock is constructed for the city of interest; this model predicts building electricity load as a function of the physical characteristics of the buildings and the weather of the city. Next, during *characterization of demand response availability*, the series of DR events to be studied and a set of typical weather conditions for the city are defined. The chosen DR events are then simulated within the building model at each of the typical weather conditions, and the difference in energy use between regular building operation and DR building operation is calculated at each weather condition. These differences represent the building stock's DR availability at each weather condition. Finally, during *electricity system optimization*, an electricity system model is used to optimize the generation, storage, and transmission assets of the city to meet the city's total electric load. Within this model, the building load curve without DR is used as an input, and the DR availabilities are used as time-variant constraints. When the model is solved, its output is the operating schedule of all generation and storage assets on the city's grid, which now include building DR. Each of these steps is described in greater detail in the following text, which applies the model framework to study the effects of DR, building efficiency increases, and expanded variable renewable energy capacity in the city of Regina, Saskatchewan.

2.1. Scenario definition

The City of Regina, Saskatchewan represents a unique opportunity for decarbonization efforts. On the one hand, current emissions in Regina are relatively high; much of Saskatchewan's electricity is generated by burning coal (Canada Energy Regulator, 2021a), making Saskatchewan's grid one of the highest-emitting in Canada (Canada Energy Regulator, 2021b). Additionally, only about 10% of buildings in Saskatchewan use electricity as their primary heating fuel, while the rest rely on natural gas and other fossil fuels (Statistics Canada, 2020a). However, Regina is also ideally poised to do something about its emissions: the city has exceptionally high wind and solar generation potential (Canada Energy Regulator, 2021a) and recently made a commitment to be powered by 100% renewable energy by 2050 (Tink & Folk, 2021).

To determine how Regina might simultaneously reduce total electricity demand and meet existing electricity demand with renewable energy, we simulate a version of Regina in which its current electric grid is supplemented with additional capacity provided by wind and solar resources. Given this grid configuration, we then compare the performance of present-day buildings to that of more-efficient buildings which are modified with increased envelope insulation and the installation of highly efficient ground source heat pumps (GSHP). Additionally, to explore one way in which building flexibility might be a useful asset in reaching Regina's decarbonization targets, we define a DR scheme based on heating setpoint changes within Regina's residential sector and then perform simulations at three different DR magnitudes, defined by degree change and event frequency. This results in a total of six scenarios, each powered by the same renewable-supplemented grid, but with a unique combination of DR magnitude and building stock configuration. These scenarios are summarized in Table 1 and are described in detail in the following paragraphs.

Present-day Regina is powered by a generation capacity of 88 MW hydro and 218 MW NG (SaskPower, 2021). To this capacity, our study adds an additional 100 MW wind farm, and outfits 25% of Regina rooftops with solar panels. These capacities were chosen because they were shown in a previous work to represent a transitional situation in which renewable capacity is large enough to experience significant curtailment at times, yet not so large that it is overbuilt (Seatle et al., 2021). Transitional situations such as this are important to explore because they represent the short-term decisions that are necessary in sequence to achieve long-term and deeper decarbonization scenarios (Smith, 2020; Rosenbloom et al., 2018). In the specific scenario for this study, an increase in renewable capacity without phasing out any traditional generation allows the grid to use VRE when available, but still benefit from the reliability of more-traditional generation resources. This modified grid configuration is used for each of the six exploratory scenarios.

Following this, the two different versions of Regina's building stock are defined. First, a *present day* version of the city is constructed using existing 2020 data. Since only 10% of homes in Saskatchewan have electrified heating systems (Natural Resources Canada, 2020), only 10% of the building stock is assumed to contribute to the city's electric heating load and participate in DR in this scenario. Second, in order to explore how increased building efficiency might impact DR, we consider the effects of high-impact building retrofits. In the literature, both envelope insulation upgrades (Feng et al., 2016; Recart and Sturts Dossick, 2022) and high-efficiency ground source heat pumps (GSHP) (Yin et al., 2019; Zarrella et al., 2020; Menegazzo et al., 2022) have been noted to have a significant impact on building energy use; thus, our *highly efficient* building stock scenario incorporates both GSHP installation and envelope retrofits to the highest tier of the BC Step Code, which represents one of the highest national standards for building envelope efficiency (Government of British Columbia, 2022; "BC Energy Step Code, ", 2021). Of note, since Regina is a heavily heating-dominated climate (American Society of Heating, Refrigeration, and Air-Conditioning Engineers, 2021), we focus solely on building heating use for this study.

Following this, to determine how the timings of demand-response events might affect the value provided to the system, a setpoint-based DR scheme is envisioned at three levels of magnitude, defined by degree change and event frequency. DR based on the changing of building temperature setpoints has long been a focus of building DR studies (LeMay et al., 2008; Zhang et al., 2013; Yoon et al., 2014; Yin et al., 2016; de Chalendar et al., 2023) and is a popular target for residential DR in North America (Sarran et al., 2021) because with the advent of smart meters it is relatively easy to incorporate DR into existing infrastructure (Vellei et al., 2021). In the literature, different studies recommend varying numbers of degrees for the temperature change as well as varying lengths of the temperature-change event. On the low end, LeMay et al. (2008) and de Chalendar et al. (2023) describe setpoint adjustments of 2–4° F (about 1–2 °C), while Xiong et al. (2022) adjusts temperature for several 15-minute intervals during the day. At the other extreme, Aliabadi et al. (2022) and Duman et al. (2021) allow setpoints to be adjusted continually throughout the day, while Vellei et al. (2021) allows temperatures to change between 3 and 6 °C and Basnet et al. (2019) performs a wide-ranging study of temperature variations up to 15° F (about 8 °C). Medium-length events seen in the literature tended to last between 2 and 4 h (LeMay et al., 2008; Yin et al., 2010; Basnet et al., 2019; Sarran et al., 2021; Vellei et al., 2021).

As our case study is meant mainly as a demonstration of the model linkage framework, we use middling values based on those seen in the literature: degree changes of 1 or 4 °C, and event length of 2–3 h. Given these values, three different scenarios are constructed to explore different aspects of the possible solution space. In the *baseline* scenario, building temperatures are dropped by 1 °C for up to 3 h in response to a grid requirement for generation. This event can occur up to 1 time per day, up to a maximum of 20 times per month. Next, in the *high-energy* scenario, building temperatures are dropped by 4 °C for 3 h. Since a 4-degree temperature change reduces energy usage by slightly more

Table 1
Setup of the 6 building-side scenarios explored in this study.

Scenario Name	*Infrastructure Parameters*		*Demand Response Parameters*				
	City Year	% of Building Stock Participating	Temperature Change (°C)	Maximum Event Duration (Hours)	Maximum Number of Events Per Day	Maximum Number of Events Per Month	Average Monthly Energy Shifted (MWh)
Baseline: Present Day	2020	10	1	3	1	20	235
Frequent: Present Day	2020	10	1	2	4	30	198
High-Energy: Present Day	2020	10	4	3	1	6	257
Baseline: Highly Efficient	2050	50	1	3	1	20	274
Frequent: Highly Efficient	2050	50	1	2	4	30	220
High-Energy: Highly Efficient	2050	50	4	3	1	6	174

than 3 times that of a 1-degree temperature change, this event is only allowed to occur 6 times per month. This ensures that a comparable amount of total energy is shifted in each case, and only the timing of when that shift occurs is varied.[1] Finally, in the *frequent* scenario, building temperatures are again reduced by 1 °C, but for only 2 h up to 4 times per day, and up to 30 times per month. In this scenario, the lowering of the event duration to 2 h is balanced out by the higher monthly maximum of 30 events per month, allowing the same approximate amount of total energy to be shifted as in the other two scenarios. Meanwhile, the increased daily maximum of 4 allows shifting to occur more frequently if that is found to be optimal.

2.2. Building model creation

The next step of our model linkage framework is the construction of the building model. For this study, we use an engineering model, which represents building energy use as a function of the physical factors directly affecting that use (Swan and Ugursal, 2009). These factors include constant thermal exchange with the environment, the energy input into heating and cooling systems to maintain appropriate temperatures, and occupant behaviours such as the use of lighting and other appliances. A larger set of buildings, such as a residential community or a city, can be represented via archetype-based aggregation, in which a few representative buildings are modelled in detail via a simulation engine, and the results are then scaled by the number of each building type to match the size of the target building stock (Ballarini et al., 2014; Reinhart and Cerezo Davila, 2016; Deng et al., 2022).

For this study, EnergyPlus (United States Department of Energy, 2021) was used as the simulation engine, and three archetypes were constructed and then aggregated to form a city-scale load curve. These archetypes were validated in Seatle et al. (2021), with the number of archetypes was selected because little difference in accuracy was seen between three- and six- archetype versions of the same model. To represent *present day* Regina, input parameters including the number of buildings of each type, building vintage, floor area, and type of heating appliance were taken from national and provincial census data (NRCAN, 2020, 2018; Statistics Canada, 2020b). For each building, thermal heat transfer properties were estimated based on its vintage according to the formulas proposed by Tooke et al. (2014). In addition, a static load curve representing plug loads such as lighting and appliance use was included based on the work of Armstrong et al. (2009), and weather information was taken from the Canadian Weather Energy and Engineering Datasets (Environment and Climate Change Canada, 2021). Parameter descriptions for the major archetypes used are given in Table 2, and a graphic depicting the flow of information through this model is shown in Fig. 2.

Following this, the *highly efficient* version of Regina was simulated by modifying the *present day* model. To simulate a highly-optimized future version of the city, all buildings were assumed to have complete envelope retrofits so that the thermal insulation properties of the windows, walls, basement, and roofs met the highest tier of the BC Step Code. As well, the thermal system of every building was assumed to be replaced with a highly-efficient ground source heat pump based on a template from EnergyPlus (National Renewable Energy Laboratory, 2022).

2.3. Characterization of demand response availability

DR events are defined and are simulated within the building model. The parameters of the DR events are based on the details of each case study scenario, and the energy differences between regular and DR building operation will be used later to inform a series of constraints within the electricity system model.

In this work, we define a setpoint-based DR event as a series of two immediately consecutive phases in which building energy use differs from what it would be in the absence of DR (Fig. 3). First, during the "generation" phase, the temperature setpoints of participating buildings are relaxed by the number of degrees specified in the case study scenario. This causes the buildings to use less energy than they would normally use; from the perspective of the electric grid, the energy difference between the regular and relaxed-setpoint energy use can be conceptualized as "generation" because additional energy is now available for the grid.

Each generation phase lasts for the length of time specified by the case study scenario. Immediately after this amount of time has elapsed, the buildings' setpoints are changed back to their original (pre-DR) value, causing the buildings to consume additional energy as the buildings heat back up; this constitutes the "storage" or "recovery" phase of the DR event. From the perspective of the electric grid, the extra energy use can be thought of as "storage recovery" – the replenishment of the building stock's thermal storage bank at the cost of some energy that could have been consumed by other end-uses. We assume that all buildings contributing to heat load participate simultaneously in both phases of each DR event.

To characterize building DR events in a way that is useful for the electricity system, we are interested in two hourly quantities of energy

[1] As seen in Table 3, the average monthly amounts of energy shifted are only roughly similar. However, the high-energy case shows consistent performance between years despite shifting the most energy of all the cases in 2020 and the least energy of all the cases in 2050. This suggests that the values are close enough for the purposes of this study.

Table 2
Defining parameters of the archetypes used for the 2020 version of the Regina. The 2050 version was based on this model, but with updated heating systems and envelope thermal properties as described in the text.

Archetype	Vintage	Floor Area (m)	Height (m)	Special Wall Features	Heating System	Envelope Thermal Properties	Number of Residences of Type
Old House	1970	9 × 12	3	None	NG forced-air furnace based on EnergyPlus template	Roof, wall, and window U-values, window solar heat gain coefficient, window-to-wall ratio, and infiltration rate calculated based on vintage according to the formula from Tooke et al (Tooke et al., 2014).	40,667
New House	2010	10 × 14	3	None			15,723
Apartment	1965	11 × 15	3	2 Walls Adiabatic			30,994

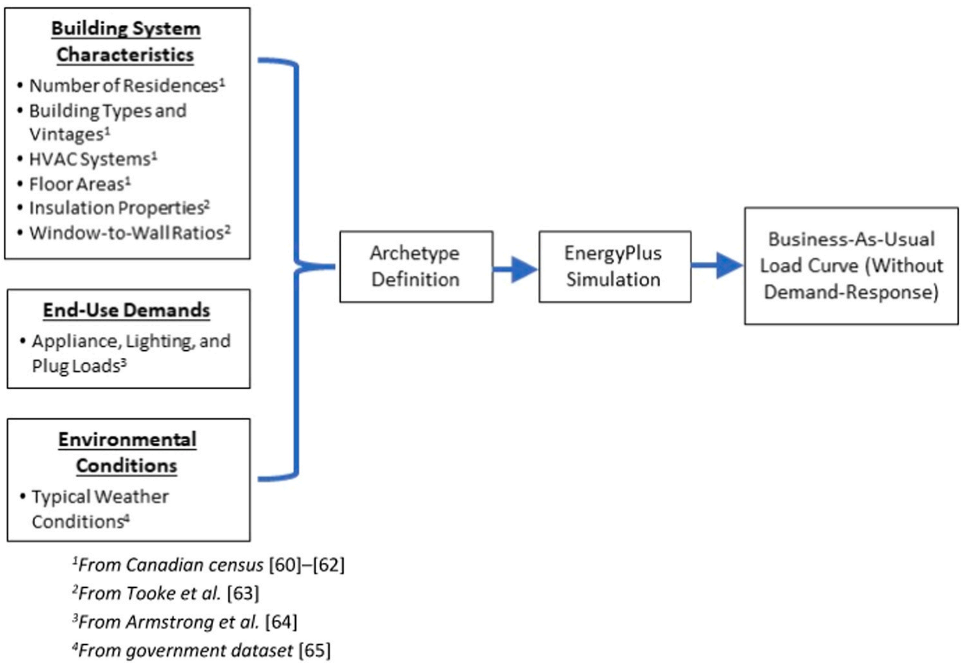

Fig. 2. **:** Information and steps used to model Regina before demand response. Main input data sources were Canadian government datasets and two supplementary research papers (leftmost column). This information was used to define a set of archetypes, which were then modelled in EnergyPlus to produce a business-as-usual load curve. [1]From Canadian census (NRCAN, 2020, 2018; Statistics Canada, 2020b). [2]From Tooke et al. (2014). [3]From Armstrong et al. (2009). [4]From government dataset (Environment and Climate Change Canada, 2021).

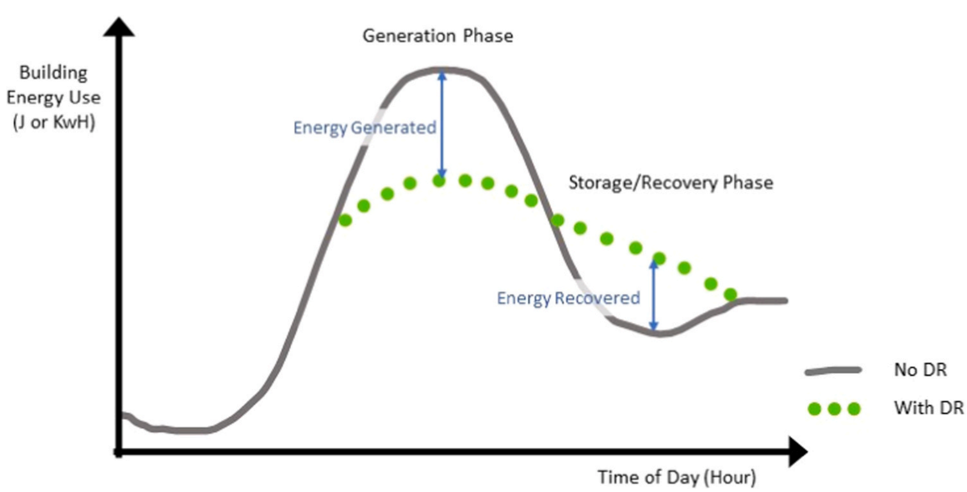

Fig. 3. Effect of our setpoint-based demand response scheme on building energy use. During the generation phase, the lowering of the buildings' heating setpoints frees up extra energy which can be used by the grid. During the storage phase, some of the generated energy is recovered, resulting in additional energy being drawn from the grid.

for each case study scenario: the energy generated during the generation phase of each DR event, and the energy recovered during the storage phase of each DR event (Fig. 3). These amounts will vary based on the outdoor temperature conditions at the time of each event, so to simplify characterization in this work we created a discrete approximation of generated and stored energy as a function of categorical weather condition. Weather condition categories were created by using the Profile feature of EnergyPlus to determine the average temperatures throughout a typical day of each month. We then grouped the months of the year based on similar temperature patterns and simulated the baseline, frequent, and high-energy DR events including sufficient recovery (enough time for all buildings to return to their pre-DR setpoint) for each group of months at two times of day: once when temperature was low but increasing, and once when temperature was high but decreasing. This resulted in eight simulated measurements for each phase of each DR strategy; for each measurement, the temperature at the beginning of the simulated period determined which months were represented by the measurement, and the direction of temperature change throughout the interval determined the time of day represented by the measurement. The eight temperature conditions and the months and times of day represented by each are shown in Table 3; the summer months of June, July, and August are excluded as the heating load during those months is negligible. Importantly, as will be detailed in the Model Validation section of this work, our categorization of these weather conditions was compared to a high-resolution simulation of the same DR events and was shown to produce similar results, which justifies their use in this work.

2.4. Electricity system optimization

In the final step of the model linkage, the differences in energy associated with generation and storage versus regular operation are formatted into a set of constraints within an electricity system model. These constraints allow the algorithm of the electricity system model to schedule generation events by deciding when, for how long, and by how much to relax building setpoints, up to the time and frequency maximums described in the case study and the energy maximums derived from the previous characterization of DR availability. To model the return of building temperatures to their business-as-usual (pre-DR) values, each generation event is followed by a recovery period in which the energy recovered is proportional to the energy shifted, based on the proportion between the generation and storage energy differences (relative to non-DR operation) observed during DR characterization. The inclusion of these generation and storage events within the electricity system model allows building DR to be scheduled by the electricity system model as if the DR capacity of the building stock was a battery.

In this paper, we use the open-source electricity system model SILVER, developed by McPherson and Karney (2017). SILVER is a production-cost model, which means that it uses linear programming to determine the optimal (least-cost) operating schedules of generators, transmission lines, and other electricity system assets in order to meet the electric demand of the modelled region (Kim et al., 2018; Håberg, 2019; Alvarez Guerrero et al., 2021). To represent Regina's electric grid, data obtained from SaskPower, the provincial electricity operator, was used to determine the system assets as well as the total demand. In addition to these, a 100 MW wind farm and a solar capacity of 353 MW (representing solar panels covering 25% of available roof space in Regina) were added to the generation mix. The available generation from these renewable assets was estimated based on weather data taken from McPherson et al. (2017).

Table 3
Characteristic temperature conditions and the months and times of day that are represented by each. Note that June, July, and August are not represented because heating load during those months is negligible.

Characteristic Temperature (°C) at Start of Simulated Period	Direction of Temperature Change During Simulated Period	Months Represented	Time of Day Represented
-20	Increasing	Jan/Dec	"Morning": 4:00 - 15:59
-14		Feb/Mar/Nov	
2		Apr/Oct	
16		May/Sep	
-12	Decreasing	Jan/Dec	"Evening:" 16:00 - midnight; midnight - 3:59
-7.5		Feb/Mar/Nov	
8.5		Apr/Oct	
19.5		May/Sep	

Model linkage between SILVER and our building model is then achieved via three key modifications to the baseline model from the original paper (McPherson and Karney, 2017):

1. As seen in Seatle et al. (2021), we directly include business-as-usual (no DR) building load from EnergyPlus as part of the hourly energy demand.
2. We introduce two new decision variables representing the hourly generation and storage status of the building stock; the ranges of allowed values for these variable were extracted from the building model during our characterization of DR availability.
3. To limit the adverse effects of building DR upon building occupants, we implement DR constraints proposed by McPherson and Stoll (2020).

A schematic of SILVER including our modifications is shown in Fig. 4, while Fig. 5 summarizes the new decision variables and constraints. The detailed mathematical formulations of the variables and the DR constraints can also be found in the Supplementary Information of this paper.

Finally, taking all of our modifications into account, the output of the solved SILVER model is a yearly operating schedule for the grid's generation assets, which now include building DR. Other parameters of interest, such as associated costs, emissions, and updated (including DR) building load are calculated based on the dispatch schedule.

3. Model validation

SIVER and the building model were both validated in previous work in the absence of DR. SILVER was developed and validated in McPherson and Karney (2017). Meanwhile, in a previous work (Seatle et al., 2021), the building model was compared to real utility data from SaskPower and found to be representative.

To determine the accuracy of the impact of DR on demand load, two sets of building load curves for the present-day building stock in the presence of baseline DR were constructed and compared. First, the direct result from SILVER was calculated by adding the demand-response component of the model's final output to the building load curve computed earlier within the model process. Second, a higher-resolution version of the DR-modified building load curve was produced by running the computed DR dispatch schedule at an individual building level within the building model. The latter calculation determines the exact amount of energy shifted and recovered during each DR event and can therefore be used as a ground truth to which the characterized events can be compared: the closer the two load curves, the better the approximation provided by the characterization method. It was found that the two load curves exhibited an R^2 value of 0.99 and differed by only 1.45% on average for each hour (Fig. 6), indicating that our characterization was a very good estimate for the available shiftable energy.

Next, our values were compared to those found in the literature. O'Dwyer et al. (2012) modelled shiftable heating load and estimated that around 75 MW could be shifted during a demand-response event

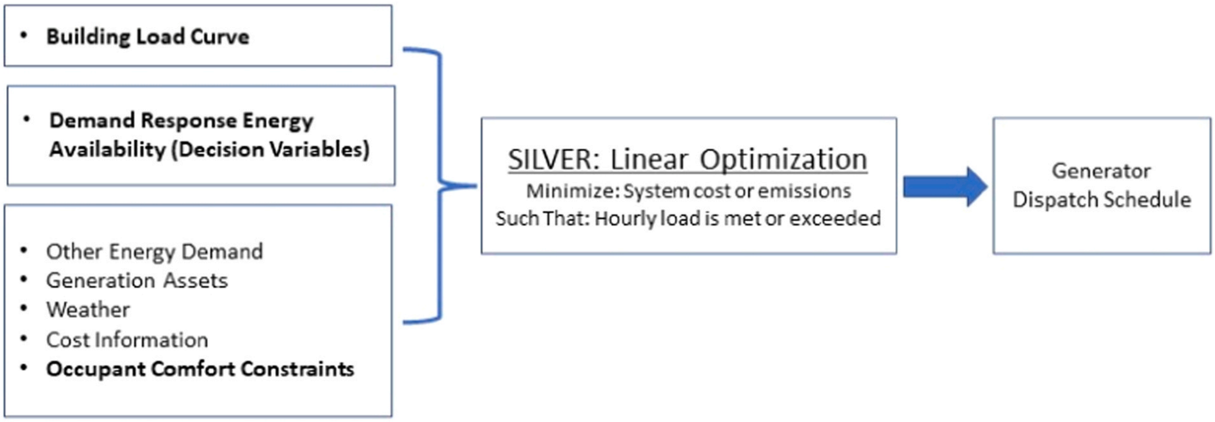

Fig. 4. Inputs and output of the SILVER electricity system model. Bold text indicates important modifications made in this paper. More information about SILVER and our modifications can also be found in a recent work by Seatle and McPherson (2024). Inputs not addressed in this work are identical to those used in Seatle et al. (2021).

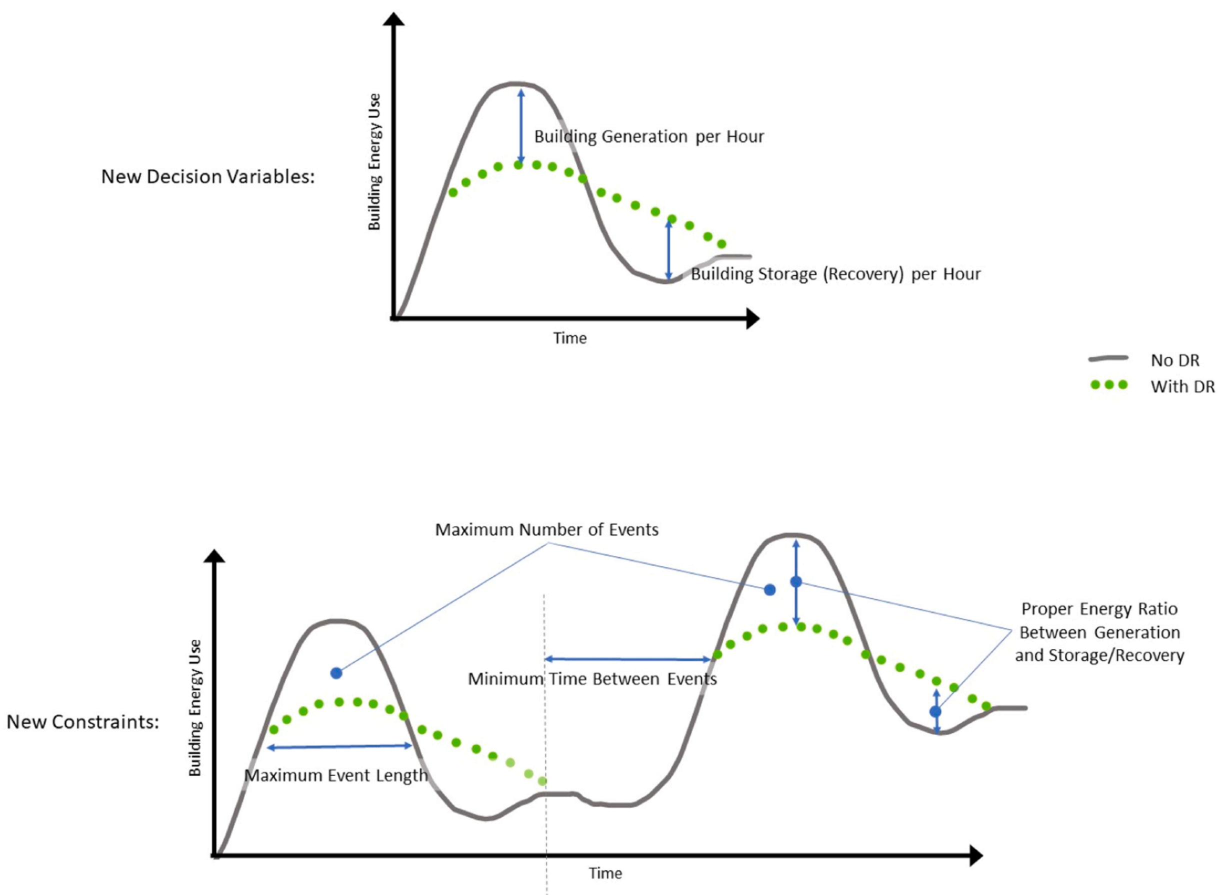

Fig. 5. Illustration of the new decision variables and constraints that were added to SILVER to represent building demand response. The decision variables specify the amount of building energy use which can be shifted via demand response, while the constraints specify the timing and frequency of demand response events.

involving 2 million homes. When scaled down to Regina's building stock count of 80 thousand, their shiftable amount comes out to 3 MW total, which is similar in scale to the 6 MW we predicted for 1-degree shifts in 2020. Similarly, Zhou et al. (2017) found that 0.12 KW per home could be shifted by cycling heating devices off for short periods during a single hour of utility load control. In our study, home energy use could be reduced by 0.75 KW per home, which is the same order of magnitude. Although our values are only within ballpark of the literature, this is acceptable because building flexibility estimates vary widely between models and scenarios – for example, Li et al. (2021) observed power reductions ranging from 0.5% to 65% of peak load among 85 papers reviewed.

3.1. Assumptions and limitations

Before discussing the results, it is important to keep in mind the limiting assumptions that were made during the modelling process. Most notable is our deterministic representation of certain aspects of the

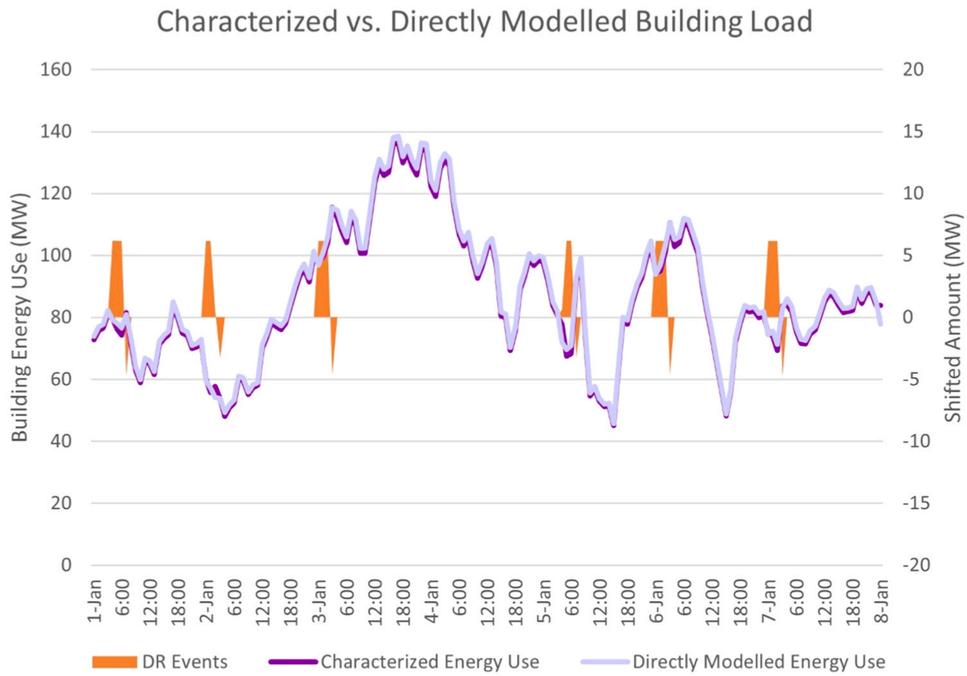

Fig. 6. Building load in the presence of demand-response events as estimated at characteristic timepoints (dark purple) versus directly simulated in the building model (light purple). Little difference can be seen between the two curves, regardless of when demand response occurs (orange).

building and electricity systems. On the building side, we assume that in the absence of DR, all buildings are kept at a constant heating setpoint of 21 °C in accordance with ASHRAE comfort standards (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2020). We further assume that all buildings have one of three non-heating electric load profiles as simulated by Armstrong et al. (2009). Similarly, on the electricity side, SILVER optimizes each month while having complete information for that month. This means that electric demand and variable renewable availability are known with 100% certainty within our model, whereas in reality, future weather and future electric demand are uncertain until they occur, and generator dispatch levels are constantly adjusted in real time based on instantaneous changes in demand and VRE availability. Across both sectors, our assumptions of set schedules with little variation between individual buildings result in a modelled grid whose operation may differ slightly from and be less complex than that of a real grid. However, by reducing the computational intensity of the model, our simplifications facilitate the novel model linkage that is achieved in this work. Additionally, over- and under-predictions of values are likely to cancel each other out when looking at a full year of operation (Routledge; ScienceDirect, 2023). Due to these factors, we assume that our assumptions are justified for the purposes of this paper.

Finally, one additional important limitation is the specificity of this study. We only investigate a few simple DR strategies, and only one type of load – heating – is impacted by those strategies. Thus, our study

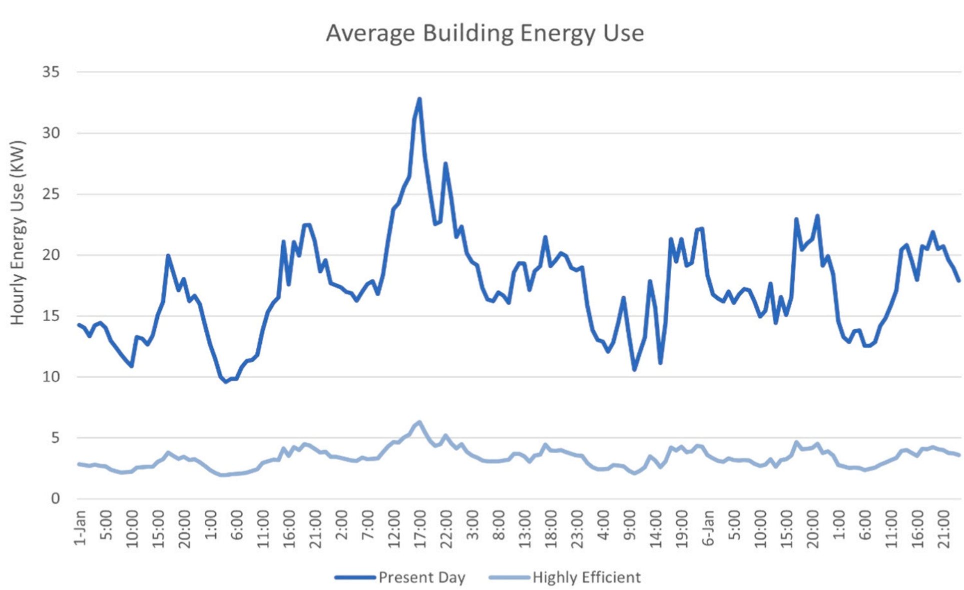

Fig. 7. Energy use for an average building from each building stock composition during one week in the coldest month of the year. Both buildings use electricity for heating.

represents only one specific case of DR. Other DR schema and the inclusion of other loads can certainly be envisioned and will be addressed in future work.

4. Results

4.1. Effects of building stock upgrades

Before DR is enacted, both building stocks perform as expected. On an individual level, the envelope and heating system upgrades result in substantial energy savings, with the average highly efficient house using around 5x less energy than the average present day house (Fig. 7). Meanwhile, as specified by the study design, both the highly efficient (assuming 50% of all homes contribute to heat load) and the present day (assuming only 10% of all homes contribute to heat load) building stocks use very similar amounts of energy (Fig. 8).

In terms of overall totals, operating costs and GHG emissions for both the present day and the highly efficient building stocks are similar, but slightly greater in the highly efficient building stock (Fig. 9). This is due to electric consumption increasing very slightly from approximately 1.84 million MWh to approximately 1.86 million MWh (an increase of 0.75%) between the two modelled years.

However, the similarity in total energy usage between the two building stocks does not translate to similar performance in the presence of DR. Within each strategy, the generation available from DR varies by time of day, building stock composition, and month (Fig. 10). Overall, the highly efficient building stock tends to have more morning availability, while the present day building stock has more evening availability. Both trends are due to the effects of increased insulation efficiency, with greater generation availability seen in whichever stock reduces consumption more during DR. Since the highly efficient buildings have more insulation, they are less able to be warmed by their environment in the morning half of the day, when temperatures are cold but increasing. This results in greater energy savings – and therefore greater amounts of shiftable energy – from DR during the mornings for this building type. Conversely, less insulation in present day buildings means that those buildings lose more heat to the environment in the evening half of the day, when temperatures are warm but decreasing; as a result, evening DR events generate more energy in present day buildings.

4.2. Effects of demand response

Overall, the cost and emissions savings associated with DR are not large on either a per-building basis, or when compared to the total operating costs and emissions. Across all investigated DR magnitudes, annual cost savings are never more than $CAD 20.21 per home, and total system operating cost is never reduced by more than 0.40%. Similarly, the largest observed annual emission reduction is only 48.5 carbon dioxide equivalent kilograms (kg CO2e) per home, and the largest percent change in emissions is only 0.42%. However, significant differences can be observed between the different DR strategies, and these can perhaps be leveraged in future work to come up with schema that are more effective than the ones proposed herein.

Comparing the overall performance of the different DR magnitudes and building stock compositions, it can be seen that high-energy shifts (changing setpoints by 4 °C) are the most effective in terms of both cost and emission savings for both the present-day (2020) and highly efficient (2050) building stocks. Shifts of this magnitude are almost twice as impactful as the other two strategies, saving a rough annual total of $CAD 200 K and 450 carbon dioxide equivalent tonnes (tCO2e) for each building stock (Fig. 11).

For the frequent and high-energy shifting magnitudes, there is little difference in performance between the two building stocks. However, performance at the baseline magnitude dramatically increases as the building stock becomes more efficient. In the highly efficient building stock, emissions savings increase from around 150 to over 300 tCO2e, while cost savings also doubled from around $CAD 65, to almost $CAD 140 K (Fig. 12).

The varying performance of the different DR magnitudes can be explained by the available shiftable energy under different conditions, the timing of DR events as a function of VRE availability, and the differential impact of DR events on NG and hydro generation.

First, although the present day buildings generally have greater generation availability during the evenings, the morning generation availability tends to be larger overall (Fig. 10), which contributes to the performance difference in the baseline case.

However, the algorithm is not always able to shift at the times with the most generation available because shifts need to align with specific timings in VRE availability. Since each generation shift is immediately followed by a recovery hour, the best timing for a shift is when

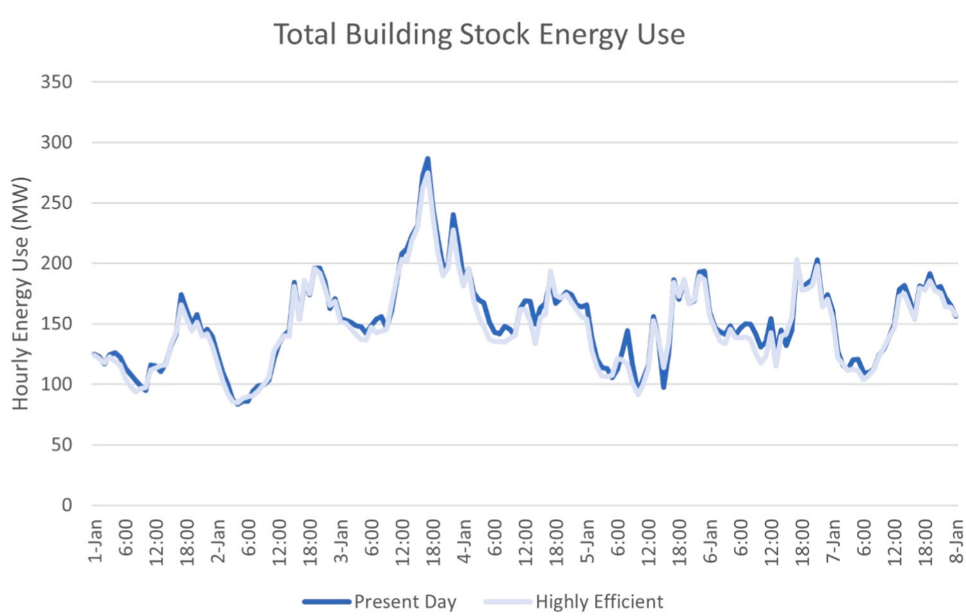

Fig. 8. Total building stock energy use during one week in the coldest month of the year. The highly efficient building stock includes a greater number of buildings to account for the higher efficiency of each building.

Fig. 9. Annual operating costs and annual emissions for the present day and highly efficient building stocks before the enactment of demand response strategies.

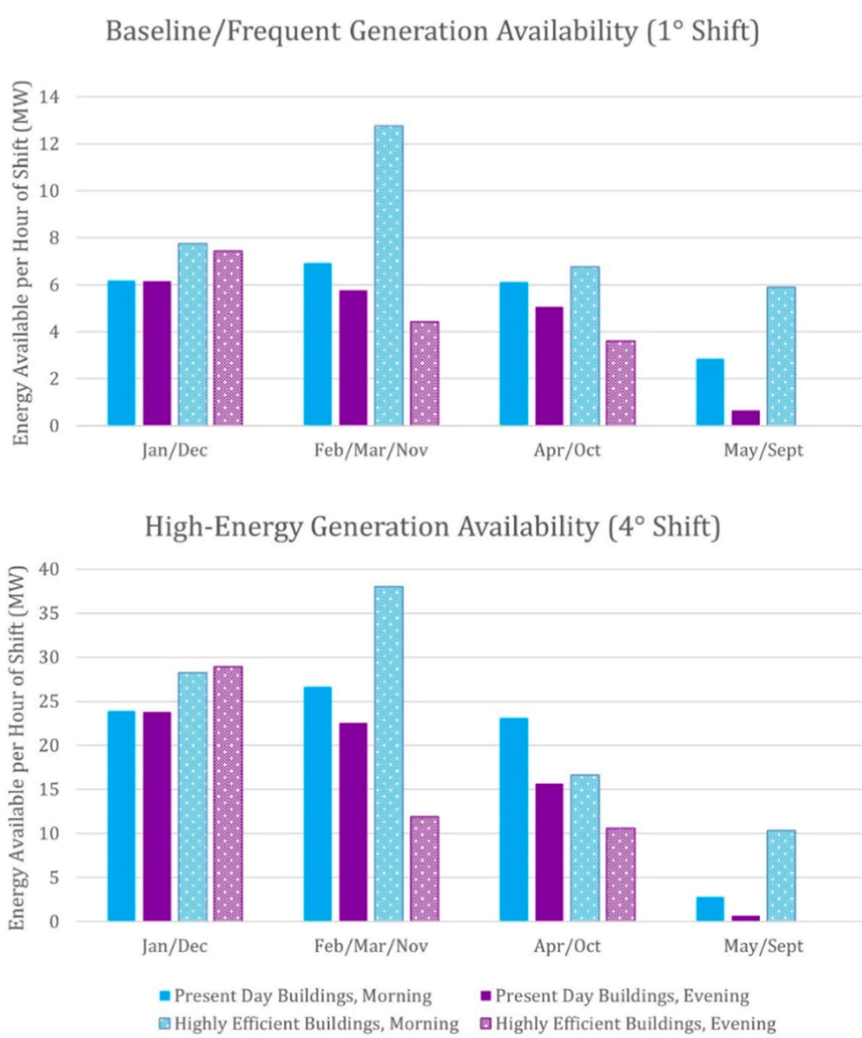

Fig. 10. Energy available for generation shift events during each hour of demand response. During the "morning" half of the day, which lasts from 4:00 until 15:59, temperatures are relatively cold but increasing. Meanwhile, the "evening" half of the day lasts from 16:00 until 3:59 the next day, and temperatures are relatively warm but decreasing. Grouped months were parameterized together and shift the same amount of energy at each time of the day; June, July, and August are not represented as heating is negligible during those months.

renewable generation is low, but will be increasing soon according to weather predictions. Thus, in addition to the frequency constraints already imposed by the various strategies, the timing of DR events is selected by the algorithm from the small pool of favourable timepoints based on VRE (Fig. 13). Since high-energy events are so infrequent, there are relatively more times at which these events can be scheduled, allowing the high-energy shifts for both building stocks to occur exclusively at times with the greatest generation availability. Frequent shifts, in contrast, are more constrained by VRE availability patterns and sometimes occur at times when the generation availability is lower,

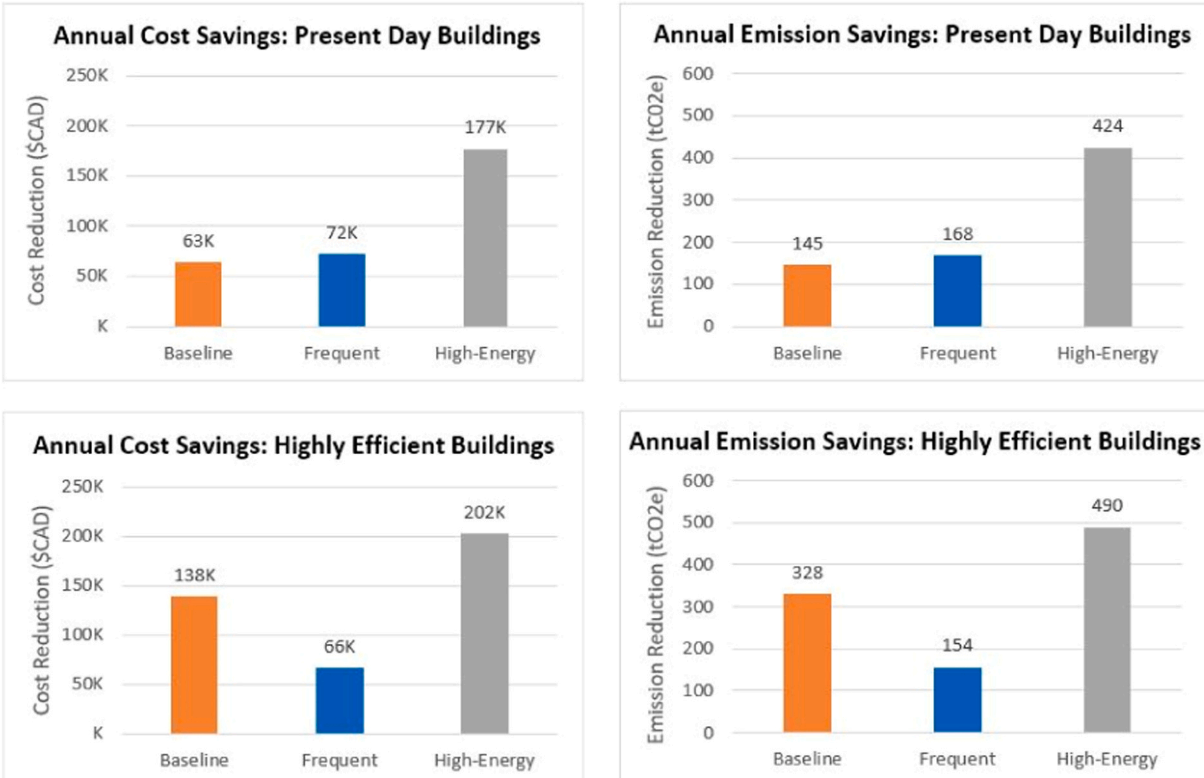

Fig. 11. Annual operating cost and emission reductions for the modelled building stocks in the presence of demand-response events of the modelled magnitudes.

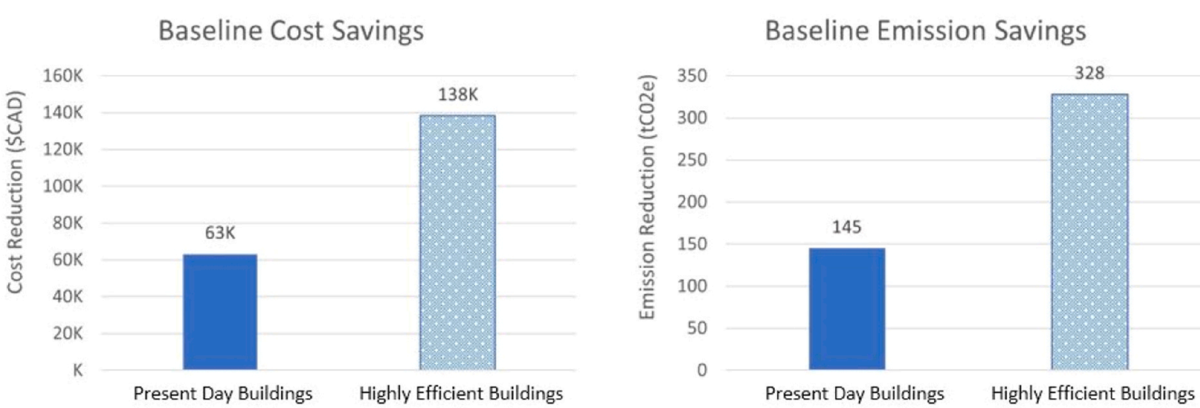

Fig. 12. Performance comparison for the baseline case between the two building stock compositions. Both cost savings and emissions savings are approximately doubled as buildings became more efficient.

resulting in poorer performance for both building stocks. At the baseline magnitude, the higher generation availability during mornings in the highly efficient building stock combined with the somewhat-smaller number of shifts (as compared to the frequent strategy) results in increased performance for the highly efficient building stock, which can preferentially shift during mornings only.

Finally, an important factor which exacerbates performance differences is how DR impacts the capacity factors of natural gas and hydro, respectively. Since NG is much more expensive per megawatt-hour than hydro, the capacity factor of NG generation is lowered in all scenarios. However, for both building stocks, frequent shifts also significantly lower the capacity factor of hydro, while the high-energy strategy has very little impact on the capacity factor of hydro (Fig. 14). This behaviour can be explained by the association of NG generators with a start-up cost. After a certain reduction in NG generation, additional reduction requires at least one NG generator to turn off and be powered on again later, incurring the start-up cost. If only a small amount of DR generation is still available, the algorithm will choose to reduce (displace) hydro, thus avoiding the start-up cost. However, if the amount of available demand-response generation is enough to offset the start-up cost, NG will be displaced instead. At the high-energy magnitude, the large amounts of energy able to be generated by demand-response in a single event enable NG generation to be displaced almost exclusively, while the small amounts of energy available per shift in the frequent strategy have the opposite effect. For the baseline magnitude, the poorer-performing present day buildings displace much more hydro than the highly efficient buildings (Fig. 14); this is a ramification of the baseline magnitude's ability to preferentially shift during the mornings when available generation is significantly higher for the highly efficient buildings than for the present day building stock.

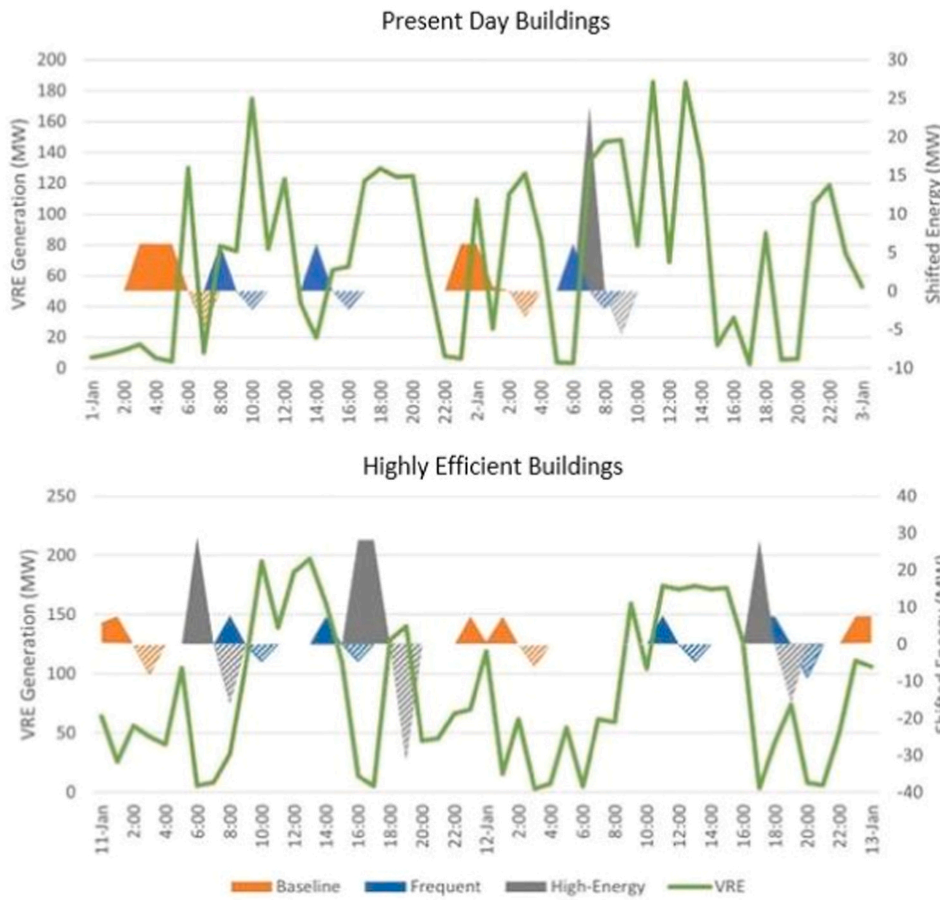

Fig. 13. Demand-response events (shading) and VRE generation (green line) in the coldest months for each building stock composition. Solid-coloured shapes (positive) represent generation events, and striped shapes (negative) represent recovery. Generation is often aligned with dips in renewable energy production.

5. Discussion

5.1. Main findings and implications

In our results, DR was successfully able to shift building energy use towards times when more renewable generation was available. However, the emission and cost reductions associated with these shifts varied based on the characteristics of the grid's more traditional generation resources. Although NG generation is more expensive and higher-emitting than hydro, NG generators are constrained by ramping limits and start-up costs when generation levels are changed. As a result, it was sometimes optimal for our scheduling algorithm to reduce the capacity factor of hydro rather than of natural gas, especially when DR shifts were smaller and more frequent. This result suggests that DR is most effective when larger amounts of energy are able to be shifted, even if this results in DR events happening less often. More broadly, this result also indicates that in transitional scenarios where renewable capacity and traditional generators are both used to meet electric demand, simply adding renewable capacity does not by itself guarantee a reduction in the emissions associated with electricity use. Rather, to ensure a maximization of emission and cost reductions, system planners must ensure that added renewable capacity is sufficient to allow inflexible fossil fuel powered generators to turn off and stay off for substantial time intervals. Exploration of whether this will be accomplished in potential future scenarios can be done through detailed modeling studies such as the one performed in this work.

The other important conclusion which can be drawn from our results is that building efficiency upgrades have mixed effects on building DR. Although DR affected both building stocks similarly at two out of the three DR magnitudes, the amounts of energy available to be shifted via DR strategies varied between the building stocks based on the time of day. This was caused by the interplay of opposing influences relating to increased building efficiency. Better envelopes allow comfortable temperatures to be maintained for longer, but they also limit passive heating and cooling at times when outside temperatures are favourable. Similarly, because more efficient heating systems require less energy to maintain comfortable temperatures, less generation can be realized by reducing temperatures a certain number of degrees, but recovery costs once a DR generation event has ended are also smaller. As our results indicate, there are no clear trends regarding the impact of building upgrades on DR availability; rather, results may vary, making it important to use models such as the one developed in this work to explore the likely impacts of proposed widespread changes to the building stock.

5.2. Impactfulness of results

In terms of total values, the results of this study are underwhelming. Because the per-building financial benefits of DR are so small, utility companies who wish to provide a financial incentive for participation in DR programs like the ones explored in this work will likely have to offer more money to consumers than the system would save by enacting DR measures. Thus, if DR programs are to become widespread, is it crucial to come up with additional motivators beyond simple financial ones. Some examples of this might include carbon credit programs which pay utilities or consumers for emission reductions, the promotion of cultural values regarding the importance of reducing carbon emissions by every little bit possible, legislation mandating DR participation, or the

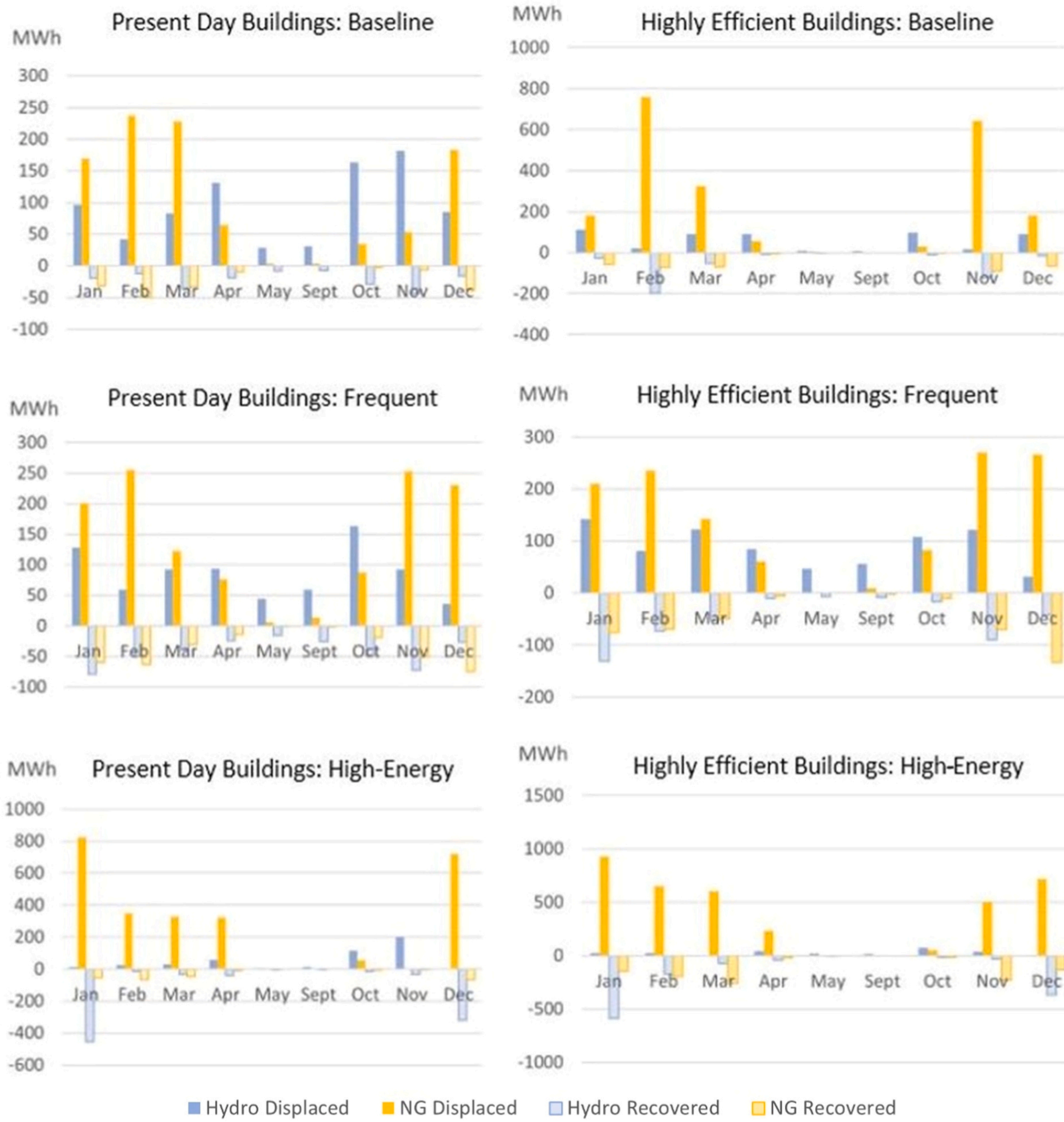

Fig. 14. Amount and type of generation displaced (positive values) and recovered (negative values) by building demand-response events of each event magnitude and for each building stock composition. June, July, and August are not shown because heating demand is negligible during those months.

development of new control strategies which are increasingly less noticeable to occupants and are thus more likely to be accepted as a normalized part of building operation.

5.3. Comparison to the literature

Several other works exhibit results that are consistent with our findings. Relating to our observed displacement of NG rather than hydro, Zhao et al (2020). noted that ramping constraints make thermal generators less flexible than pumped hydro, leading to potential cost increases when variable renewables are prioritized in the generation mix. Similarly, Imcharoenkul and Chaitusaney (2022) found that as renewable penetration increases, the inflexibility of coal and NG leads to these generators being less affected by DR programs than other, more-flexible non-VRE sources. As well, Péan et al. (2018). compared a price signal and an emissions signal for scheduling DR events and found that although both of these decreased both the costs and the emissions associated with grid operation, the price-based signal produced a greater price decrease at the expense of some emissions savings. On the topic of varied results due to changes in building stock characteristics, Satchwell et al. (2020). found that increasing envelope efficiency sometimes increased and sometimes decreased DR availability, and that the timing of building energy demand – and especially whether building demand coincides with VRE generation – is important for determining the associated costs and emissions. Finally, Salo et al. (2019). investigated several demand-response strategies and found that the most effective involved substantial (43–50%) peak power limiting, which reduced internal temperature significantly; this supports our result that shifting more energy at once is better than smaller, more frequent shifts.

5.4. Limitations and future work

This work has two main limitations: its simplicity and its scope. As discussed earlier, our building model in particular is quite simple, as only three different archetypes are modeled in detail. However, when compared with real data, little difference in accuracy was seen between a three-archetype and a six-archetype model of the city of Regina. Further, the main contribution of this paper is cross-sectoral model linkage; although more detailed modeling is certainly possible, the city-level output and the detail used for each archetype in this paper make our current model a sufficient stand-in for a generic building model in the context of model linkage. Future iterations can easily build upon our work by adding more archetypes and more detailed load modeling.

Regarding the scope of this work, we focus quite specifically on one type of load (heating) and a few DR strategies. Therefore, future work should investigate different shifting strategies and include other potential sources of flexibility. Alternative shifting strategies could include preheating buildings when VRE is high, staggering setpoint changes rather than shifting every building simultaneously, and cycling heating devices on and off for short periods of time. Meanwhile, there are a plethora of other sources which could be investigated for additional flexibility. On the building side, some examples of DR involving time-shiftable household appliances such as washing machines and dryers are seen in Luo et al. (2020), Anvari-Moghaddam et al. (2015), and Li et al. (2022), all of which describe constraints that enforce appliance energy use in the context of optimized energy management for single buildings. Another way to incorporate appliance usage is through non-intrusive load decomposition as seen in Zhao et al. (2019), Salani et al. (2020), Lin et al. (2023), and Ou et al. (2023), in which signal processing is used to extract appliance load profiles from aggregate electricity use data. These load profiles could then be used to write appliance-usage constraints that could be included within the electricity system model. Beyond buildings, there are also existing technologies which can improve grid performance and even reduce flexibility requirements. Most notable of these is battery storage; although some energy will always be lost when converting to and from a stored form, battery storage has been shown in works such as Seatle et al. (2021) to be extremely useful for capturing excess VRE for later use. Finally, one other example of a way to improve overall system performance is the use of a dynamic thermal rating system, in which the capacity of transmission lines changes based on current weather conditions. As seen in Teh and Lai (2019) and Lai and Teh (2022a, 2022b), dynamic thermal rating often increases transmission capacity since non-dynamic rating of transmission lines must account for unlikely worst-case scenarios Teh et al. (2017); as a result, use of this technology would provide greater mitigation against fluctuations in generation and demand by being able to import energy from further away.

6. Conclusion

Despite the close relationship between building electric demand and electric grid performance and emissions, models which represent both sectors in operational detail are rare, making it difficult to study how DR, building electrification, and increased building efficiency might affect the electric grid which powers those buildings. In this work, we close this gap by enacting a novel computational linkage between an operational building stock model and a unit commitment/production cost model of an electricity system. The two models are linked via two points of information transfer: first, the building load curve is used as a direct input into the electricity system model. Second, a series of DR events are simulated within the building model, and the energy differences between normal and DR operation are used as constraints within the electricity system model, allowing building DR events to be scheduled within the electricity system model as if the building stock was an energy storage bank. This linked model framework is then applied to a case study covering two building stock compositions (existing and modified) and three DR magnitudes (defined by degree change and event frequency) in the city of Regina, Saskatchewan.

In addition to the methodological contribution accomplished by our linked model framework, the results of our case study provide some insight into how building DR might impact an electric grid. To maximize the value of DR on a grid with high VRE penetration, system planners need to account for the behaviour of the traditional generators which will be curtailed when VRE is high. One way to achieve this is to schedule DR events which shift larger amounts of energy, as these types of shifts allow inflexible fossil fuel powered generators to turn off and stay off for periods of time significant enough to warrant the increased costs associated with changing fossil fuel generation levels. However, on a per-building level, the emission and cost reductions achieved by the DR strategies employed in this work were small, which necessitates either the existence of supporting policies, or the development of broader DR schemes encompassing multiple load types.

In the longer term, as building envelopes and heating systems increase in efficiency, our results also explore how these efficiency increases might impact DR. Rather than identifying any clear trends, our results show that efficiency upgrades have varied effects on the DR availability of the affected buildings: high-efficiency envelopes and heating systems can sometimes increase and sometimes decrease DR availability, depending on existing differences between indoor and outdoor temperatures. The lack of a clear pattern here indicates that although the benefits of DR may not be large, they are also unlikely to go away as building technology improves. This makes it worthwhile to invest in the development of more impactful DR strategies, which can be done through continued scenario exploration using linked model frameworks such as the one developed in this work.

In conclusion, through the novel model linkage proposed herein, computationally-inexpensive parameterization of yearly demand response availability, and exploration of scenarios relating to both demand response event magnitude and building stock upgrades, this work provides an important contribution to both methodological literature and policy applications. We hope that researchers and policymakers alike can use our results and modelling framework to answer important questions relating to residential building efficiency, DR, and renewable energy integration.

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CRediT authorship contribution statement

Stanislaw Lauren: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **McPherson Madeleine:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Seatle Madeleine:** Writing – review & editing, Software, Data curation.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Madeleine McPherson reports financial support was provided by Mitacs Canada. If there are other authors, they 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

Some data is confidential, but the rest is available upon request. Please see the Data Availability Statement within the manuscript.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.egyr.2024.01.063.

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