Modelling and Assessment of Cloud Based Smart Dual Fuel Switching System (SDFSS) of Residential Hybrid HVAC System for Simultaneous Reduction of Energy Cost and Greenhouse Gas Emission Under Smart Grid Infrastructure

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Abstract

A cloud-based Smart Dual Fuel Switching System (SDFSS) of a residential hybrid system of electric air source heat pump (ASHP) and natural gas furnace for simultaneous reduction of energy cost and greenhouse gas emission was developed. Detailed modelling, simulation, and optimization of a residential house in Ontario, Canada, was conducted to examine such smart cloud-based supervisory control potentials under different conditions such as time-of-use electricity price and federal carbon tax schemes. Maximizing energy cost saving and reducing greenhouse gas (GHG) emissions while providing a flexible and ubiquitous mechanism for utilities to control their infrastructure for load management under the smart grid framework was the primary focus of this work. This paper performed extensive simulation work supported by data analytics to estimate how GHG reduction targets 30% and 80% for 2030 and 2050. Subsequently, the study proposed a basis of modelling and policy framework to offer future low-carbon alternatives.

Introduction

To minimize the unfavourable impacts of climate change, the United Nations Framework Convention on Climate Change (UNFCCC) urged a new concession called Paris Agreement (UNFCCC, 2019). This agreement aimed to unite all the countries for a single cause to commence determined combat for climate change, find ways to reduce greenhouse gas (GHG) emissions and lead the developing countries in the subject matter. After signing this agreement, Canada also introduced the Pan-Canadian Framework on Clean Growth and Climate Change to promote the same campaign nationwide. In common with the Paris Agreement, the Pan-Canadian Framework supports innovation and technology to battle climate change and find efficient energy solutions. This framework is also strictly concerned about GHG emissions agreeing with the Federal Government of Canada, which has recently introduced taxes for carbon pollution. Besides, the Pan Canadian Framework has set an ambitious target to reduce GHG by 30% by 2030 and by 80% by 2050, relative to 1990 levels (PCFCGCC, 2019).

The breakdown of Canadian GHG emissions by the sectors is shown in Figure 1, demonstrating that the residential sector produces a significant portion of GHG emissions.

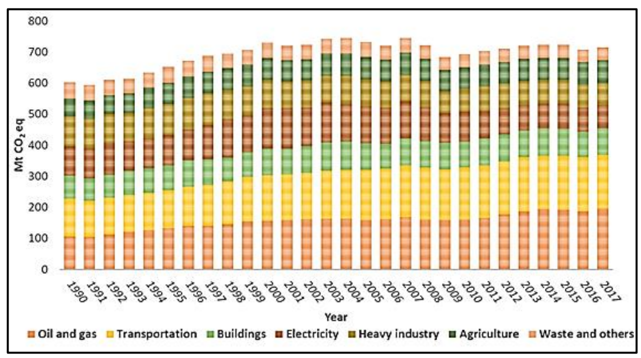

Figure 1: The breakdown of Canadian GHG emissions by economic sector from 1990 to 2017 (NRCan, 2017)

Concurrently, the residential sector's heating demand takes up to 60% of the total household energy consumption (NRCan, 2017), which justifies that energy consumption in buildings is a pivotal contributor to this problem. Figure 2 shows the breakdown of residential GHG emissions.

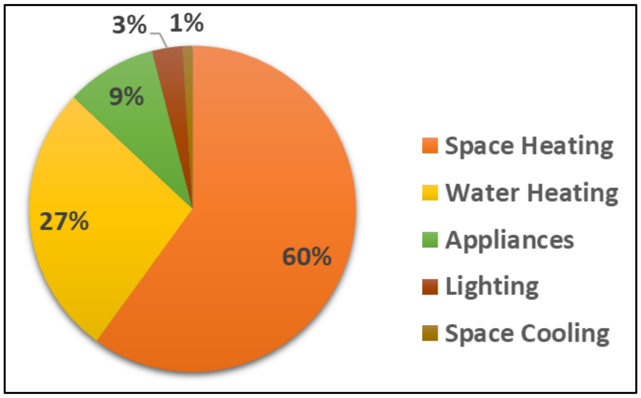

Figure 2: The breakdown of residential GHG emissions (NRCan, 2017).

According to NRCan, Canada met over 64% of the heating demand for heating with natural gas or heating oil (NRCan, 2017). Meanwhile, a combination of North American's cold climate condition and poor/old-fashioned HVAC control undoubtedly contributes to higher energy consumption and the increase in GHG emissions. Moreover, Canada Green Building Council (CaGBC) established a building code enhancement that accounts for a 3-year strategic plan. One of the government's strategic plans is to promote systems and technologies that minimize natural gas/fossil fuel usage and increase clean electricity usage in reducing GHG emissions. Even though the governments and researchers agree on being fossil-free as soon as possible, there is still room for development to achieve this end goal. It is an undeniable fact that the concerns regarding the acceleration of GHG emissions and increasing energy demand in the residential sector necessitate the continued development of efficient systems and control strategies in terms of reducing both operational and energy costs. Therefore, it is crucial to introduce technology to deal with this transition period before being carbon neutral.

For Canada to meet its commitments by 2030 and 2050, the usage of low fossil fuel must devote effort to residential heating from natural gas. On the other hand, using only electricity to meet the heating/cooling demands of the residential buildings is not technically and economically feasible now, as electricity is relatively more expensive than natural gas in Canada. Therefore, a neutral standpoint that is attaining acknowledgment is the usage of a hybrid electric air-source heat pump (ASHP) and natural gas (NG) furnace system, seen as a compromise between cost and a clean environment (Yu et al. (2019), Demirezen et al. (2019a, 2019b).

Although numerous research work has been conducted for managing the energy demand, Smart Dual Fuel Switching Systems (SDFSS) are rarely found in the literature. Alibabaei et al. (2016) and Alibabaei et al. (2017) discussed three strategies for operating the energy demand of an archetype house through the optimal utilization of an electric ASHP and a natural gas-fired mini-boiler using a predictive controller. In Demirezen et al. (2019), a working cloud-based SDFSS prototype was implemented and tested for a one-year period in 2018 to cover the entire heating and cooling seasons. The house is in Strathroy, Ontario, Canada, and is evaluated to be a nearly zero-energy house (NZEH).

This paper aims at studying the effects of this newly developed SDFSS on reducing GHG emissions while considering the economic impacts of the electricity and NG consumption from the HVAC equipment to address the knowledge gap in the literature. The overall model proposed in this research includes the TRNSYS house model, which simulates the annual space heating demand of the research house, and the optimization model of the SDFSS. The results are demonstrated as a series of summary tables on yearly energy consumption, energy cost, and GHG emission for the study house under different time-of-use (TOU) electricity prices and federal carbon tax schemes with highlights of 2030 and 2050 GHG emission reduction targets. Other heating sources and different switching systems, including standard natural gas, setpoint switching to natural gas at -15°C, setpoint switching to natural gas at -5°C, setpoint switching to natural gas at 0°C, the system with only ASHP and the SDFSS. The SDFSS was found to reduce the energy cost when compared with the other switching systems analysed.

Case Study Description

The Toronto and Region Conservation Authority (TRCA) Archetype Sustainable Twin-Houses (ASH) demonstrate sustainable housing technologies for experimentation and research. In Figure 3, the house to the left is called House-A, while the house on the right is called House-B. These houses are designed, constructed, and equipped to display current and future sustainable technologies.

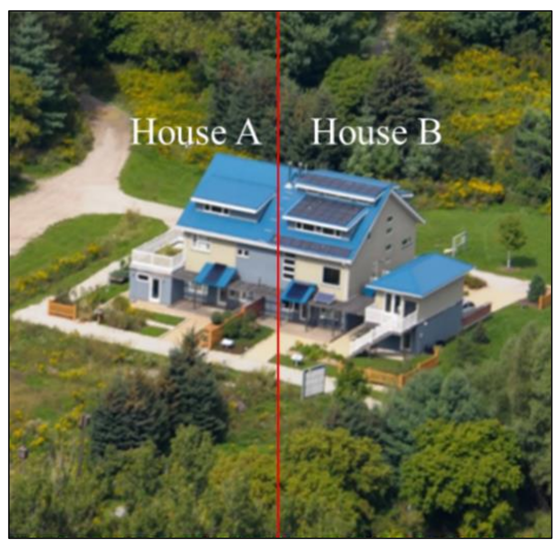

Figure 3: South–west side of twin houses at Toronto and Region Conservation Authority.

This research focuses on House-B that was constructed to have an air-tight building envelope according to the requirements of ASHRAE 90.1 (Safa et al., 2015). House B of the TRCA Archetype building is equipped with various mechanical systems such as an NG furnace, two ASHPs, and a residential hot water heater for two individual SDFSSs to be developed, implemented, and analysed. Recently, data mining from the first SDFSS is being conducted. Therefore, this paper depicted the simulation results. The cloud-based SDFSS developed operates based on the temporal thermal demand of the house and optimizes its HVAC operation, using short-term weather forecast information to minimize the operating cost for the next few hours on the cloud server. It then communicates with the house's HVAC system via a connected smart thermostat to operate either the ASHP or the auxiliary heater, in this case, an NG furnace for the first SDFSS and a residential water heater for the second SDFSS. The ASHP operates as an air-conditioning system during the cooling season. The performance variation with partial load was considered when identifying the operation mode. The ASHP defrost was considered. Hence, the ASHP was disabled to operate below the balance point temperature. In addition to a computer platform developed to mimic and observe the behaviour of SDFSS, the physical communication interface board was developed to test the existing system. The developed method iterates an algorithm consisting of various temporal parameters such as time and day, TOU price of electricity, outdoor temperature, air-source heat pump performance/capacity, natural gas furnace performance, and thermal demand of the house to select the most cost-effective fuel source for the given hour. The TOU electricity pricing scheme for the weekdays is demonstrated in Figure 4. Furthermore, holidays and weekends are included in off-peak hours.

Table 1: TOU hours during the weekdays.

Time Range	Summer	Winter
0:00-7:00	Off-Peak	Off-Peak
7:00-11:00	Mid-Peak	On-Peak
11:00-17:00	On-Peak	Mid-Peak
17:00-19:00	Mid-Peak	On-Peak
19:00-24:00	Off-Peak	Off-Peak

Methodology

The SDFSS modelled, developed, and implemented at the studied house accounts for the following factors in deciding whether NG furnace or ASHP to be operated at a specific time to meet space heating demand of the house:

- π_{TOU}: TOU electricity price which changes based on hour of the day such as off-peak, mid-peak, on-peak hours
- π_{NG}: Natural gas price (which is constant during the day)
- *COP*: Coefficient of performance of the ASHP which is derived from the manufacturer's data and then calibrated with experimental data
- η_n: Efficiency of the NG furnace (90% with multiple measurements on site)
- NG energy density: 10.395 kWh/m^3 (Government of Ontario 2018)
- T_{amb}: Ambient outdoor dry bulb temperature

To estimate HD of the house, a TRNSYS model was developed. The house model is demonstrated in Figure 4.

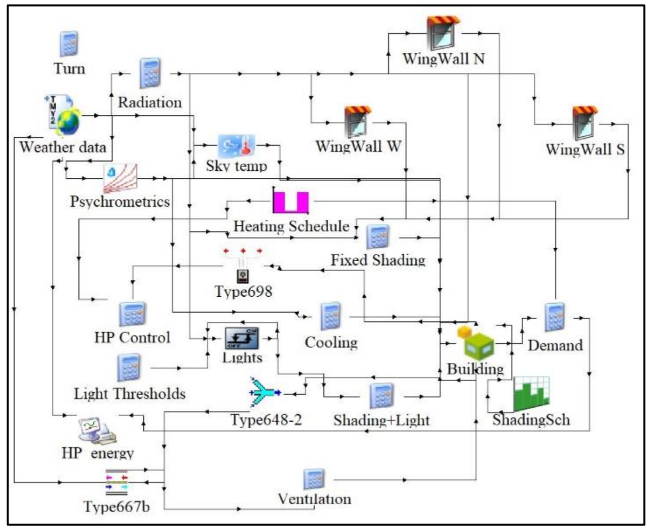

Figure 4: House model in TRNSYS Studio.

The simulation spans over a year to obtain the annual heating load in this study. The weather data used for simulation is the typical meteorological year (TMY) for the location of the house. Figure 5 depicts the hourly outdoor temperature with a maximum of 33.1ºC and a minimum of -22.27ºC. The heating season started from January 1st (1st hour) to May 22nd (3408th hour) and from October 1st (6576th hour) to December 31st (8761st hour). The indoor setpoint temperature is adjusted to 21ºC for the heating season as it is the actual setpoint temperature of the thermostat. The hourly heating load from the TRNSYS simulation for the year is given in Figure 5.

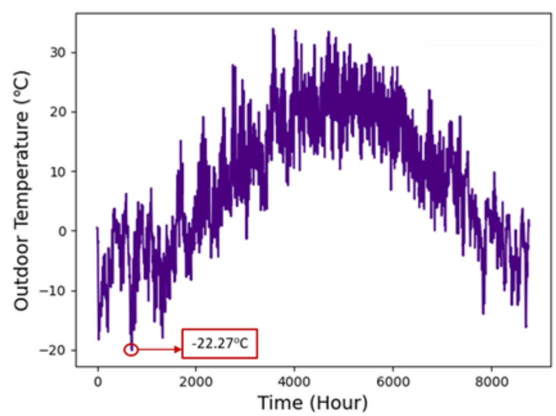

Figure 5: Annual hourly outdoor temperature.

Moreover, from the simulation of the TRNSYS model, the peak heating demand was estimated to be 9.16 kW and the total annual space heating load of the house was estimated to be 15,442 kWh. Simulated hourly heating demand is shown in Figure 6. It is noted that the hours where the load is zero continuously is the cooling season.

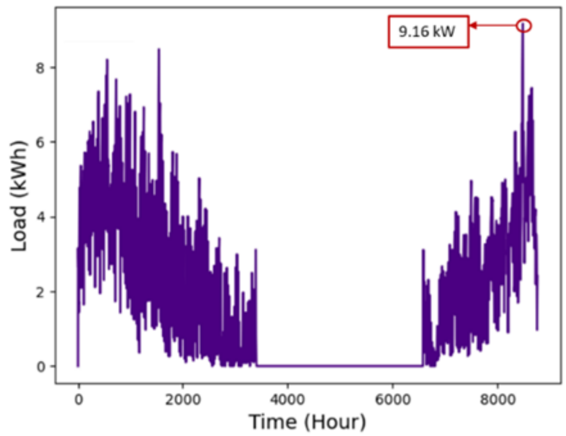

Figure 6: Simulated hourly heating demand.

To use the parameters from the ASHP in the SDFSS algorithm, the COP and capacity curves are created as follows:

Minimum Capacity = $8E\text{-}06x^4 + 0.0001x^3 - 0.0055x^2 + 0.0022x + 5.9551$ (3)

Maximum Capacity = $5E\text{-}06x^4 + 0.0004x^3 + 0.0031x^2 + 0.0036x + 11.1$ (4)

Minimum COP = $-2E\text{-}06x^4 - 9E\text{-}05x^3 - 1E\text{-}04x^2 + 0.0843x + 2.8588$ (5)

Maximum COP = $-2E\text{-}06x^4 - 4E\text{-}05x^3 + 0.003x^2 + 0.1035x + 3.3598$ (6)

where, x is the location specific ambient temperature. The ASHP used in the study is a variable capacity cold climate heat pump which can provide the appropriate amount of heating and cooling without frequently turning on and off. The hourly heating demand from the TRNSYS model is compared with the maximum capacity of the ASHP. If the heating demand exceeds the maximum capacity of the ASHP, then the maximum capacity is used to estimate the electricity load. The supplementary heater, in this case, an NG furnace, is used to fulfil the heating demand when the maximum capacity of the ASHP is not sufficient. Based on these curves, the electricity consumption from the ASHP is calculated. Equation 7 considers the hourly cost of electricity consumption for the residential heating system. Equation 8 calculates the hourly cost of natural gas consumption if the NGF were to operate independently.

$$e_c = E\pi_{TOU} \tag{7}$$

Where: e_c = Hourly cost of electricity ($)
E = ASHP electricity consumption (kWh)
π_{TOU} = Marginal pricing of electricity per kWh ($/kWh)

$$n_c = N\pi_{NG} \tag{8}$$

Where: n_c = Hourly cost of natural gas ($)
N = Furnace natural gas consumption (m^3)
π_{NG} = Marginal price of natural gas per m^3 ($/kWh)

ASHP electricity consumption and the furnace/boiler natural gas consumption are derived as follows:

$$E = \frac{H}{COP} \tag{9}$$

Where: H = Space heating demand
COP = Coefficient of performance of ASHP

$$N = \frac{H}{U_n} \times \frac{1}{\eta_n} \tag{10}$$

Where: u_n = Natural gas energy density (kWh/m^3)
η_n = Efficiency of NGF/boiler (%)

The hourly cost of the HVAC operation varies based on the fuel source (natural gas or electricity) selected. The total annual cost is the summation of the sum of effective natural energy cost and the sum of effective electricity cost from the ASHP, which is demonstrated in Equation 11 as follows:

$$c_T = \sum e_e + \sum n_e \tag{11}$$

Where: c_T = Total annual operating cost ($)
e_e = Effective electricity cost ($)
n_e = Effective natural energy cost ($)

The hours that the ASHP was operating was multiplied by the TOU cost of electricity to obtain the effective electricity cost (e_e). Similarly, the hours of NG based HVAC equipment such as NGF in operation was multiplied by the hourly cost of natural gas to calculate the effective natural gas cost (n_e).

The SDFSS algorithm is iterated in an hourly basis. The algorithm has an hourly decision mechanism which selects the fuel source to be operated based on their hourly cost. The cheaper source for its corresponding hour is activated for that specific hour.

GHG emissions are reduced by default when using any heating source other than the NGF as electrical heating emits less GHGs than fuel-based systems. Using Ontario's hourly GHG emission factor for grid-supplied electricity, which tends to be far cleaner than natural gas, allows a demonstrated reduction in emissions relative to NGF-only systems and other options. Equation 12 calculates GHG emission from natural gas, and Equation 13 calculates the same for electricity consumption.

$$GHG_n = D_{NG} \times N \tag{12}$$

Where: GHG_n = Hourly GHG emission from natural gas consumption (kg)
D_{NG} = GHG density for natural gas (kg/m^3)

$$GHG_e = D_E \times N \tag{13}$$

Where: GHG_e=Hourly GHG emission from electricity consumption (kg)
D_E=density for electricity consumption (kg/kWh)

U_n, natural gas energy density was taken as 10.395 (kWh/m^3) (Government of Ontario, 2018) for the unit conversion of the GHG_n. The GHG emission intensity of natural gas was taken as 1.863 kg/m³ (NRcan, 2018b).

The SDFSS decides whether ASAP or NG furnace to be in operation based on the cheapest total cost amongst effective electricity and natural gas costs. The data-driven SDFSS model consisted of an optimization algorithm that ran hourly. The methodology used in this study is summarized as follows:

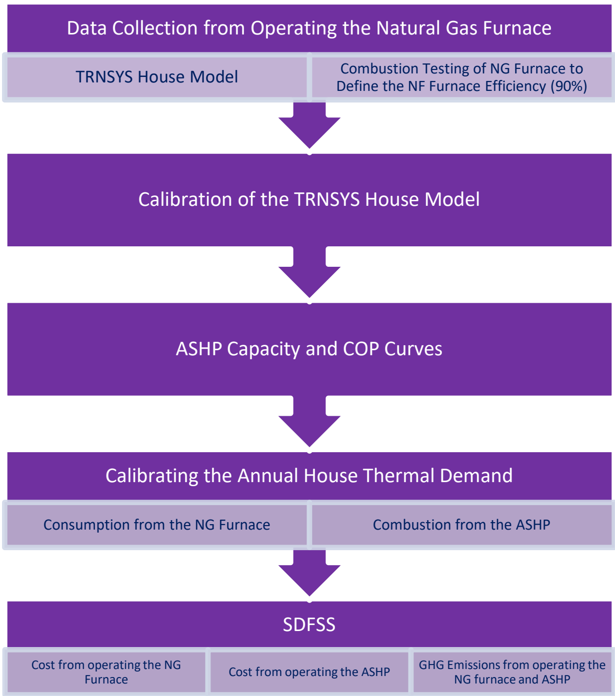

Figure 9: The summary of the procedure followed in this paper.

Results

Smart Dual Fuel Switching System

From the equations introduced, the annual energy consumptions for the studied equipment were calculated. The average hourly GHG emission factors (in gCO_2eq/kWh) from (Ontario Grid, 2018). Along with the TOU dependency based on heating and cooling season, the weekends and statutory holidays are considered as the off-peak hours for the operation of the ASHP. Therefore, the day of the week and these holidays are also included in the analysis.

A detailed analysis of the outcomes of the SDFSS in terms of cost (in $) and GHG emissions released (in kg) are included. The COP and capacity of the ASHP depend on the ambient outdoor temperature, and this is the reason why most of the HVAC manufacturer has a built-in temperature sensor on their ASHP (Ye et al., 2020). The ambient outdoor temperature of the specific location of the house is required in defining and meeting the thermal demand of the house (Demirezen et al., 2020). Therefore, the ambient outdoor temperature is a pivotal factor in this analysis to observe smart switching optimal temperatures based on the introduced algorithm of the SDFSS. The ASHP used in this study runs down to -25ºC, and this limit of the ASHP is included in the algorithm. Table 2 depicts the marginal TOU electricity pricing based on TOU tiers such as off-peak, mid-peak, and on-peak hours (Ontario Energy Board, 2018). The electricity prices from the consumption of electricity from ASHP are calculated based on these criteria. However, the fixed NG marginal price is $0.3038/m^3.

Table 2: Marginal TOU electricity pricing.

TOU Tier	Electricity Pricing
Off-peak	$0.9219/kWh
Mid-peak	$0.1237/kWh
On-peak	$0.1624/kWh

In addition to standard residential TOU electricity pricing schemes, a federal carbon tax (CT) of $10 to $250/tonne of CO_2 is included in the analysis with an iteration of $10/tonne of CO_2 increment.

Comparison of the SDFSS and Other Heating Systems

The simulation platform is created to observe the viability of the SDFSS algorithms and compare those with the conventional heating methods such as natural gas furnace only heating. Moreover, the manufacturer's default switching points (fixed thermostat switching settings), such as at 0ºC, -5ºC, -10ºC, and -15ºC from the natural gas furnace to the ASHP and from the ASHP to the natural gas furnace is compared with the SDFSS.

The electricity consumption from the ASHP and the consumption from the NG furnace can be examined in the same unit, while NG energy density is introduced as 10.395 kWh/m^3. After calculating the annual energy consumptions from the HVAC equipment such as the ASHP and the NG furnace, the energy factors are introduced for all the heating methods as follows:

$$\mathrm{EF} = \frac{HD}{AC_{ASHP}+AC_{NG}} \tag{14}$$

where;

- Energy Factor: EF
- Annual space heating from the TRNSYS Model = *HD* (kWh)
- Annual consumption from the ASHP (kWh) = AC_{ASHP}
- Annual consumption from the NG furnace (kWh) = AC_{NG}.

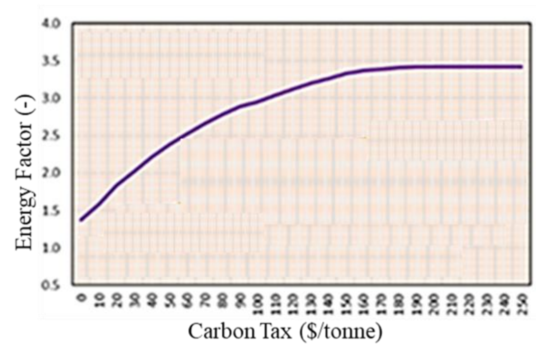

Figure 10: Annual energy factors (-) in comparison to carbon tax ($/tonne).

By the introduction of the federal CTs, it is observed that the NG prices increase dramatically, prompting the SDFSS algorithm to switch from NG to the ASHP more frequently.

From the annual energy factors demonstrated in Figure 10, it is observed that the SDFSS has the highest factor when there is $140/tonne CT or more is introduced.

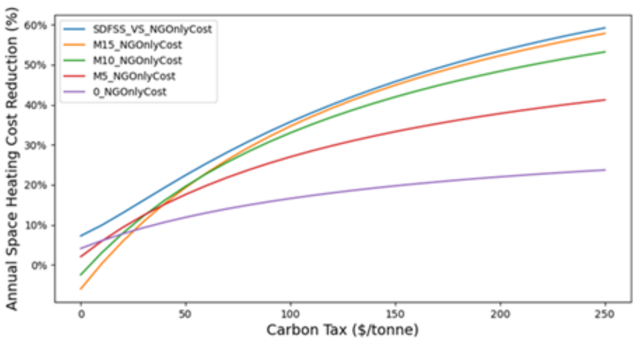

Figure 11: Annual space heating cost reduction (%) as a comparison to NG-only system versus CT for the systems studied.

Figure 11 denotes that the SDFSS always offers the most reduction in cost in comparison to other systems studied.

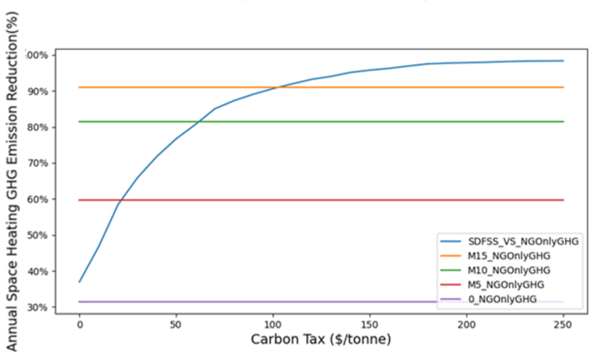

Figure 12: Annual space heating emission reduction (%) as a comparison to NG only system versus CT for the systems studied.

According to Figure 12, it is observed that all the systems outperform the NG-only system in terms of their being more environmentally friendly with lower overall annual GHG emissions. Moreover, the SDFSS as heating can accomplish the ambitious targets of reducing GHG emissions by 2030 and 2080 by 30% and 80%. Without implementing the CT, 30% of GHG reduction is observed with the SDFSS compared to the NG-only system. When $80/tonne CT is introduced, the GHG emissions reduction to 80% by using the SDFSS compared to the NG-only system.

Conclusion

This study introduced a unique and innovative approach to tackle the balance between economic (energy cost) and environmental (related GHG emission) of the residential space heating in a cold climate) by proposing a flexible, cost-effective, and clean energy solution. The technology, called the SDFSS, was developed, installed, and implemented at a house in Vaughan, Ontario, Canada. The SDFSS estimates the optimal switching point temperatures by accounting for various temporal factors such as TOU electricity prices, the efficiency of the natural gas furnace, coefficient of performance and capacity of the ASHP, and natural gas prices. This study focused on the environmental and economic impact of implementing such alternative technology, called cloud-based SDFSS, for a hybrid residential HVAC system, in the transitioning period of prior being completely fossil-fuel free. The preliminary analysis demonstrated that the implemented SDFSS is a cost-effective, flexible, and environmentally friendly alternative to conventional HVAC equipment used in North American cold climates.

In addition, this paper examined the potential benefits, in terms of reduction of operating cost and GHG emission, of such cloud-based SDFSS for hybrid residential HVAC system in meeting different GHG emission reduction targets by 2030 and 2050 with the recently introduced federal carbon taxes (CTs) of $20, $30, $40, and $50/tonne of CO_2 from 2019 to 2022. Moreover, the CTs from $0/tonne to $250/tonne with an increment of $10/tonne CT are analysed in detail.

The future work will include other types of ASHP with different operational limits. Furthermore, the future work will study different locations and residential houses within North America.

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