

Seamlessly Fuel Flexible Heat Pump with Optimal Model-based Control Strategies to Reduce Peak Demand, Utility Cost and CO₂ Emission

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ABSTRACT

This research develops a novel hybrid fuel heat pump system for space heating of residential and small commercial buildings with built-in optimization and control. Whereas conventional dual fuel systems either run on gas or electricity at any given moment, the proposed seamlessly fuel flexible heat pump (SFFHP) simultaneously consumes gas and electricity and continuously optimizes the proportion of each. The building air flows across the heat pump condenser first and then flows across the furnace coil, and this reduces the heat pump temperature lift. The SFFHP delivers energy savings by allowing each subsystem (gas furnace and electric heat pump) to operate where it performs best to improve energy efficiency, minimize energy cost, and minimize carbon footprint.

The capacities of the electric heat pump and gas furnace are continuously adjusted based on ambient conditions, utility price signals, and marginal grid emission signals. An optimal model predictive control strategy was developed with the goal of minimizing utility cost and minimizing CO₂ emission. Two case studies were conducted to simulate the performance of SFFHP during the heating season in Chicago and Los Angeles, respectively. Compared with a conventional electric heat pump, SFFHP yields 33% utility cost reduction and 49% CO₂ emission reduction in Chicago. Similarly, it achieves 23% utility cost reduction and 17% CO₂ emission reduction in Los Angeles. Case studies demonstrate that SFFHP can deliver significant reductions in peak demand, utility cost, and CO₂ emission. Due to the hybrid fuel nature of this novel equipment, user comfort will always be maintained. The fuel flexibility makes it an attractive option for demand response programs.

Key words: Heat pump, dual fuel, fuel flexible, grid responsive, hybrid heat pump, CO₂ reduction

Introduction

In response to global warming and climate change, the United States has implemented policies and technical efforts that include the use of renewable energy and the increase of energy efficiency to reduce energy consumption and greenhouse gas (GHG) emissions. The first executive order signed by President Joe Biden's administration in 2021 streamlined the milestones to reduce the carbon footprint of the US building stock by 50% before 2035 and ensure the US achieves a 100% clean energy economy and reaches a net-zero emission society no later than 2050. Although the ultimate carbon reduction goal is to eliminate fossil fuels, it is important to increase the efficiency of existing fossil fuel-based building equipment in the transition period to zero emissions. The more effective use of existing fuel-powered device will allow significant reductions in GHG emissions and energy waste. One promising equipment which shows a good compromise

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between economic and environmental impacts in the transition period is the dual fuel heat pump (DFHP) consisting of an electric heat pump (HP) and a natural gas furnace (Yu et al. 2019).

For a conventional DFHP, during extremely cold weather when the HP capacity and efficiency drop, auxiliary heat is provided by a fossil-fuel furnace. The furnace kicks in when the outdoor temperature reaches the balance point where it is cheaper to fire up the furnace than operate the HP at low efficiency and low capacity. Depending on the HP and heating load of the space, this balance or switching point usually ranges from -10°C to -15°C . The switching point can either be fixed at the thermostat or at the HP control board. The furnace can be powered by natural gas, oil or propane. HP saves energy because pumping heat uses less energy than producing heat. The efficiency of the advanced furnace ranges from 90 to 96% while recent advances (Munk, Shen, and Gehl 2021) in cold climate heat pumps show that HP can achieve 4.5 in terms of coefficient of performance (COP) at 8.3°C outdoor temperature, 3.0 COP at -8.3°C , 2.5 COP at -15°C and 1.8 COP at -26.1°C .

The electricity sector has seen a shift from traditional centralized system to a smart grid device (Alibabaei et al. 2017). This phenomenon has been ushered in by the increased integration of renewable energies. The rapid proliferation of the ‘Internet of Things’ (IoT) (Siano 2014) allow major loads, such as heat pumps, to be controlled with the goal of reducing peak power consumption on the electrical grid. In a smart grid, heat pumps can be considered part of the demand side that can be actively managed to stabilize voltage fluctuations caused by high demand or high penetration of renewable energy (Fischer and Madani 2017). With smart control of DFHP, the system can switch between furnace and heat pump mode depending on the outdoor temperature, gas and electricity prices, desired indoor temperature, renewable energy generation, and heat pump’s COP (Siano 2014). The smart switching controls between furnace and EHP have been conducted in literature (Demirezen and Fung 2021). In this paper, model predictive control (MPC) was used to reduce GHG emissions and optimize the HVAC equipment’s energy cost. The MPC was formulated and applied on a Smart Dual Fuel Switching System (SDFSS) prototype.

It is important to describe how to incorporate a grid’s GHG (greenhouse gases) condition into a site-specific MPC. The grid system-wide emission rate in a specific grid region depends on the total power production rate from grid power generators, and other factors that affect system operating conditions, such as weather. The marginal operating emissions rate (MOER) is the partial derivative of the systemwide emission rate with respect to the total production rate (Callaway, Fowlie, and McCormick 2018). It means the change of the emission rate in the grid region with respect to the last megawatt produced by dispatchable generators having the unit of metric Ton CO₂-equivalent per MWh [mTonCO₂e/MWh]. Intuitively, this indicates how much carbon emission rate increases/decreases in a grid region when one consumes one megawatt more/less. Therefore, MOER allows for associating the power usage at a specific site with the carbon emission rate in the grid region by simply multiplying the on-site power consumption with the MOER signal.

In this paper, we used the MOER signal calculated by WattTime, based on a proprietary model that extends the basic methodology used by (Siler-Evans et al. 2013) and (Callaway, Fowlie, and McCormick 2018), but adapted for real-time use. WattTime calculates these marginal operating emission rates in real-time, every 5 min using a combination of grid data from the respective ISO and 5 years of historical Continuous Emissions Monitoring System data (Agency 2018). Figure 1 shows a demonstration of WattTime data on June 29th 2021 in California.

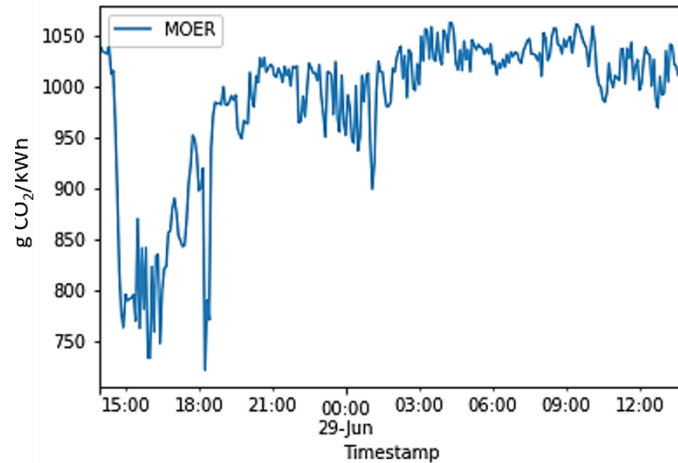


Figure 1: Demonstration of Marginal Grid Emission Data from WattTime (June 29th 2021, California)

Whereas conventional dual fuel systems either run on gas or electricity at any given moment, this study introduces a novel hybrid fuel heat pump which simultaneously consumes gas and electric power. It continuously optimizes the proportion of each, and thus, is called the Seamlessly Fuel Flexible Heat Pump (SFFHP). SFFHP uses a modular communication interface to adjust the capacities of the electric heat pump and gas furnace continuously based on utility price signals, marginal grid emission signal, fuel cost, weather data, and equipment modeling results. By heating the process air first across the heat pump condenser, and then across the furnace coils, the heat pump temperature lift is reduced. This results in energy savings by allowing each subsystem (gas furnace and electric heat pump) to operate where it performs best by utilizing the optimized combination of gas and electricity. Figure 2 shows the schematic of SFFHP. The detailed control strategy to regulate heat pump and furnace subsystems is explained in next section.

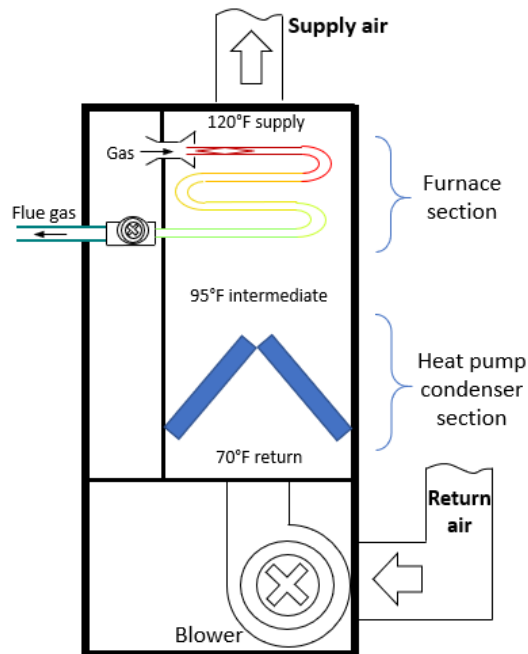


Figure 2: Schematic of Seamlessly Fuel Flexible Heat Pump (SFFHP)

The remaining part of the paper is organized as such: section 2 describes the simulation model and optimal model predictive control strategy development of SFFHP. Section 3 demonstrate the efficacy of SFFHP with two case studies in Los Angeles and Chicago. Section 4 summarizes the findings.

Methodology

SFFHP uses several different parameters such as weather data, natural gas price and electricity utility pricing, marginal emission rate, and equipment performance predicted by the system model to regulate SFFHP operation. This research develops multi-objective control optimization to regulate the heating capacity of furnace and EHP in a small time frame with the goal of saving operational energy cost and reducing GHG emission. As shown in Figure 3, SFFHP is a grid-responsive appliance with the intent of deciding the most cost-effective and environment-friendly operation strategy.

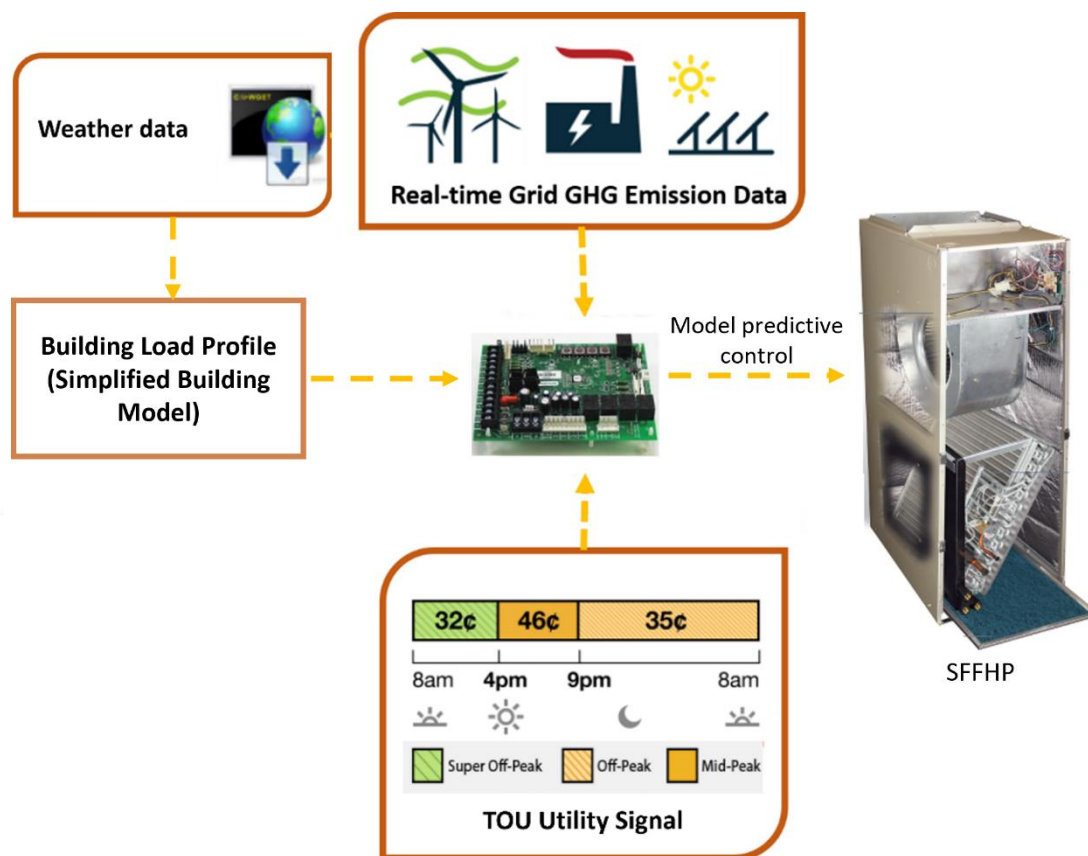


Figure 3: Optimal model-based control architecture of SFFHP

System Simulation Model

To model the performance of heat pump and gas furnace, DOE/ORNL Heat Pump Design Model (HPDM) (Shen and Rice 2016) is used. HPDM is a public-domain HVAC equipment and system modeling and design tool which supports a free web interface and a desktop version for public use. In this study, a 3-ton cold climate heat pump is used as the sub-system of SFFHP. The rated heating capacity is 10.55 kW in heating mode and 10.64 kW in cooling mode under AHRI

210/240 test standards (AHRI 2008). Figure 4 shows the performance of the heat pump at different outdoor temperature. This model is validated against experiment data (Munk, Shen, and Gehl 2021). The natural gas furnace is a commercial product with 1200 CFM as maximum air flow rate and 95% as the rated Annual Fuel Utilization Efficiency (AFUE). The natural gas energy density used in the simulation is 10.395 kWh/m³.

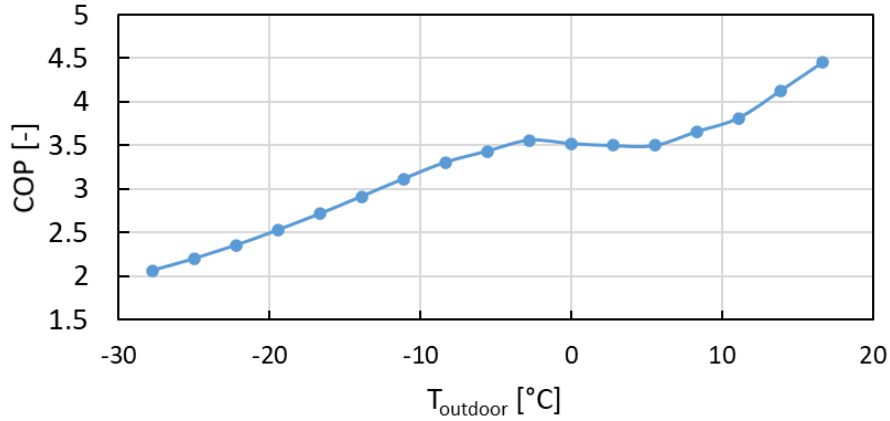


Figure 4: Performance of 3-ton electric heat pump

Optimization Problem Formulation

Genetic Algorithm (GA) implemented in MATLAB is used to solve the capacity distribution of the two sub-systems, i.e., electric heat pump and furnace, at each time step. The two objectives of optimization are to minimize the utility cost of heating season and minimize the total CO₂ emission as shown in Equation (1).

$$\begin{aligned}
 \text{Objective - 1: Minimize} & \left(\sum_{t=\text{Start of Heating Season}}^{\text{End of Heating Season}} \text{Utility Cost}(t) \right) \\
 \text{Objective - 2: Minimize} & \left(\sum_{t=\text{Start of Heating Season}}^{\text{End of Heating Season}} \text{GHG Emission}(t) \right)
 \end{aligned} \quad (1)$$

Equation (2) calculates the utility cost at each moment of a day. In Equation (2), $\text{Ratio}_{\text{HPtoTotal}}$ is the design variable in the optimization problem. $\text{Ratio}_{\text{HPtoTotal}}$ refers to the ratio between the capacity of heat pump to the total capacity of SFFHP. $Q_{\text{building}}(t)$ is the building heating load obtained from EnergyPlus (Crawley *et al.* (2001)), $\text{COP}_{\text{HP}}(t)$ is the coefficient of performance of electric heat pump predicted by HPDM. $\text{price}_{\text{electricity}}$ and $\text{price}_{\text{naturalGas}}$ is the Time-of-Use electric price and natural gas price, respectively. η is the furnace efficiency.

$$\text{Utility Cost}(t) = \frac{\text{Ratio}_{\text{HPtoTotal}} \times Q_{\text{building}}(t)}{\text{COP}_{\text{HP}}(t)} \times \text{price}_{\text{electricity}}(t) + \frac{(1 - \text{Ratio}_{\text{HPtoTotal}}) \times Q_{\text{building}}(t)}{\eta_{\text{furnace}}} \times \text{price}_{\text{NaturalGas}} \quad (2)$$

Similarly, the emission at each time step is calculated in Equation (3). The first term on the right side of Equation (3) is the emission of heat pump and the second term is the emission of

furnace. $Emission_{GridMarginal}(t)$ is the marginal emission grid signal from WattTime. $Emission_{NaturalGasPerkWh}(t)$ is the gas emission density, i.e., 179.6 gCO₂/kWh.

$$Emission(t) = \frac{Ratio_{HPtoTotal} \times Q_{building}(t)}{COP_{HP}(t)} \times Emission_{GridMarginal}(t) + \frac{(1 - Ratio_{HPtoTotal}) \times Q_{building}(t)}{\eta_{furnace}} \times Emission_{NaturalGasPerkWh} \quad (3)$$

The multi-objective optimization is conducted using weighted sum method. Equation (4) shows how to calculate the fitness value of a control strategy. The w_1 and w_2 are weights specified by the user. The relative values of the weights reflect the different priorities of different objectives. The optimal designs are achieved through minimizing the fitness value. Because the weighted sum method depends on comparing the values of different objectives, those values usually have different units and/or different orders of magnitude. It is necessary to normalize the objectives. Equation (4) also shows how to normalize the utility cost and the emission.

$$\begin{aligned} \text{Normalized Objective-1: } UtilityCost^{norm} &= \frac{UtilityCost(Ratio_{HPtoTotal}) - UtilityCost_{min}}{UtilityCost_{max} - UtilityCost_{min}} \\ \text{Normalized Objective-2: } CO2Emission^{norm} &= \frac{CO2Emission(Ratio_{HPtoTotal}) - CO2Emission_{min}}{CO2Emission_{max} - CO2Emission_{min}} \\ \text{fitness} &= w_1 \times UtilityCost^{norm} + w_2 \times CO2Emission^{norm} \\ \text{where } w_1 + w_2 &= 1 \end{aligned} \quad (4)$$

The upper and lower bounds of utility cost and emission amount cannot be known before running the optimization; however, the approximated values of those limits are sufficient to maintain the objectives in the same order of magnitude (Arora (2004)). In this study, those upper and lower limits are obtained by preliminary optimization runs. It is worthwhile to mention that this simulation uses historical MOERs as if they were forecasted MOERs. The main purpose of this case study is to demonstrate the efficacy of SFFHP to reduce carbon footprint and utility cost when it is operated according to TOU and MOER signals.

Los Angeles Case Study

The performance of SFFHP is first evaluated using Los Angeles TMY-3 weather data from November 1st, 2019, to February 29th, 2020. Figure 5 shows dry bulb temperature at each hour of these 4 months. The thermostat set temperature is specified as 65 °F in heating season. If the ambient temperature is above 65 °F, space heating device will not operate.

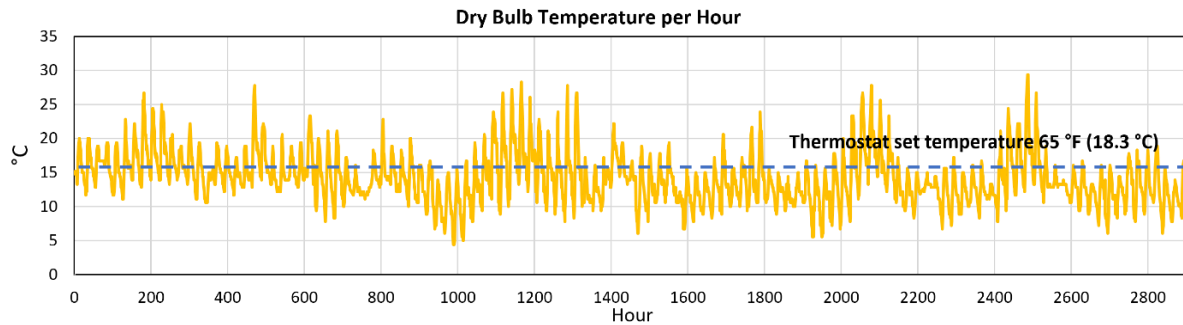


Figure 5: Dry Bulb Temperature for Each Hour of Los Angeles from November 2019 to February 2020

Figure 6 shows the marginal grid carbon dioxide (CO₂) emission data from November 2019 to February 2020 for the area administrated by Los Angeles Department of Water and Power.

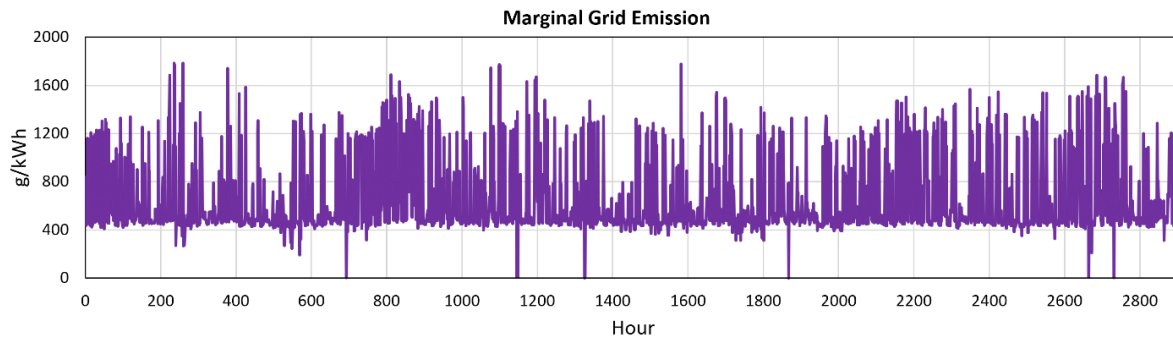


Figure 6: Marginal Grid CO₂ Emission for Each Hour of Los Angeles from November 2019 to February 2020

Time-of-Use utility rate is adopted from Southern California Edison (SCE) and the natural gas price is adopted from SoCalGas (Figure 7). The electricity price ranges from 25 to 44 cents per kWh, while the gas is only 4.27 cents per kWh.

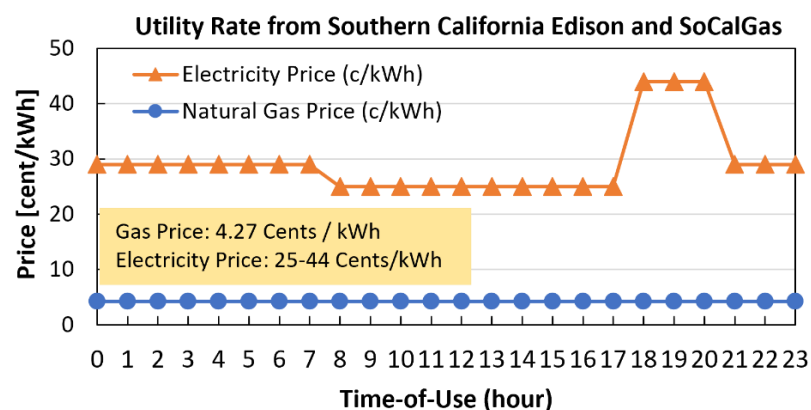


Figure 7: Time-of-Use Utility Rate from Southern California Edison (SCE) and Gas Price from SoCalGas

Figure 8 shows the Pareto Front for the optimal performance of SFFHP operated under the MPC strategy. A Pareto Front of a multi-objective optimization shows all the optimal designs in objective space. Different performance points represent different operation strategies for SFFHP by varying the weights on the two objectives (Equation (4)), i.e., either to be more emission-reduction oriented or to be more operation-cost-reduction oriented. As indicated by the Pareto Front, running furnace alone is the cheapest option due to the significant lower gas price.

Two performance points, ‘Opt-medium’ and ‘Opt-LowCO₂’, are sampled from the Pareto Front. Opt-medium is in the middle of Pareto Front, and it has compromised performance between utility saving and emission reduction, while Opt-LowCO₂ yields the most significant CO₂ emission reduction. Compared with a conventional heat pump, when SFFHP is operated under ‘Opt-medium’ control strategy, it yields 22.9% utility cost saving with only 2.5% more CO₂ emission. When SFFHP operated under ‘Opt-LowCO₂’ strategy, it yields 4.2% utility cost reduction and 17.3% CO₂ emission reduction compared with the electric heat pump.

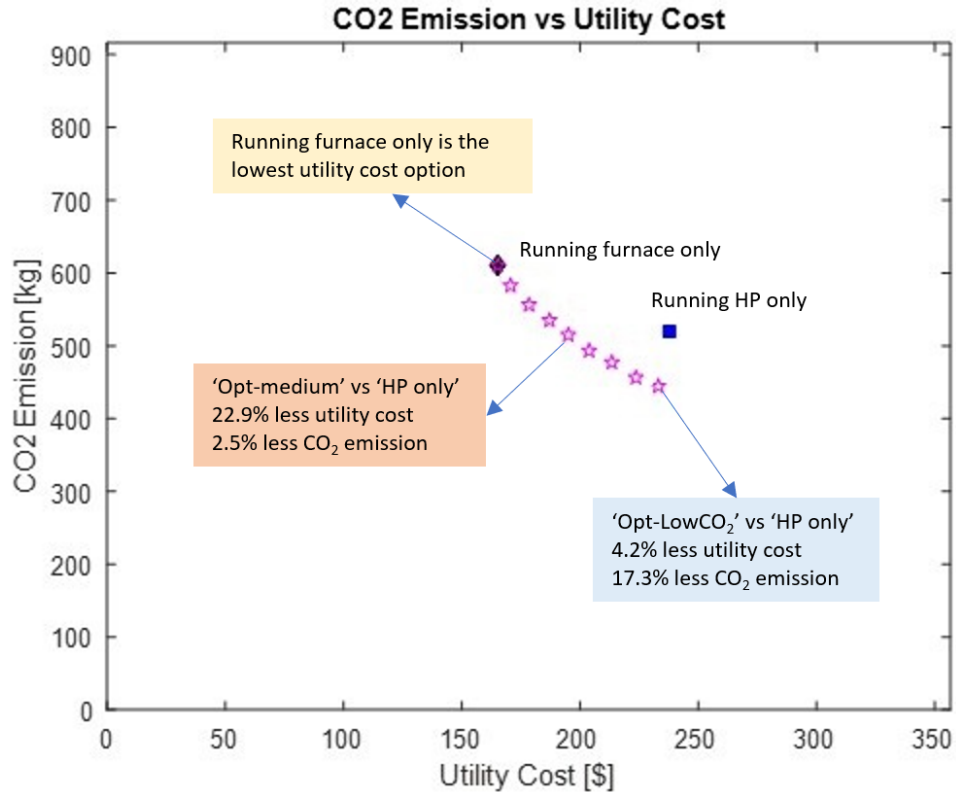


Figure 8: Pareto Front for SFFHP Performance Operated using the Optimal Control Strategies in Los Angeles

Analysis of a Single Day in Los Angeles

To get more insights on the results and investigate the daily performance of the system, the coldest day in heating season is further analyzed. Figure 9 shows the outdoor dry bulb temperature in Los Angeles on December 12th, 2019. The average temperature is 9.6 °C. Figure 10 shows the marginal grid CO₂ emission of that day for each hour.

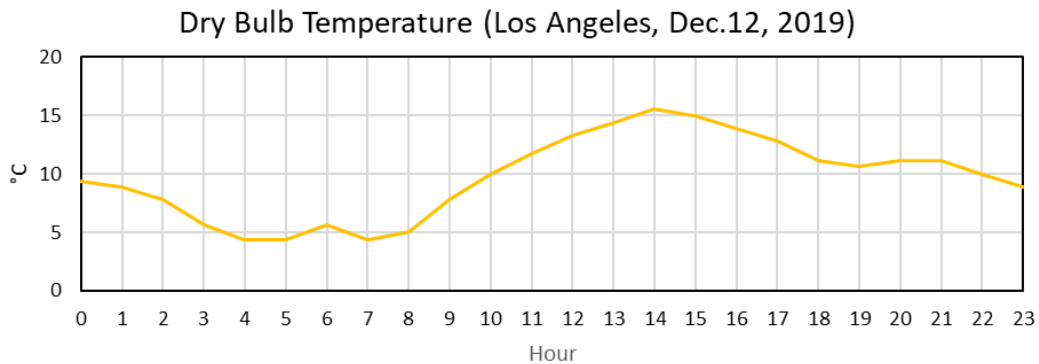


Figure 9: Outdoor Dry Bulb Temperature in Los Angeles, Dec. 12th, 2019

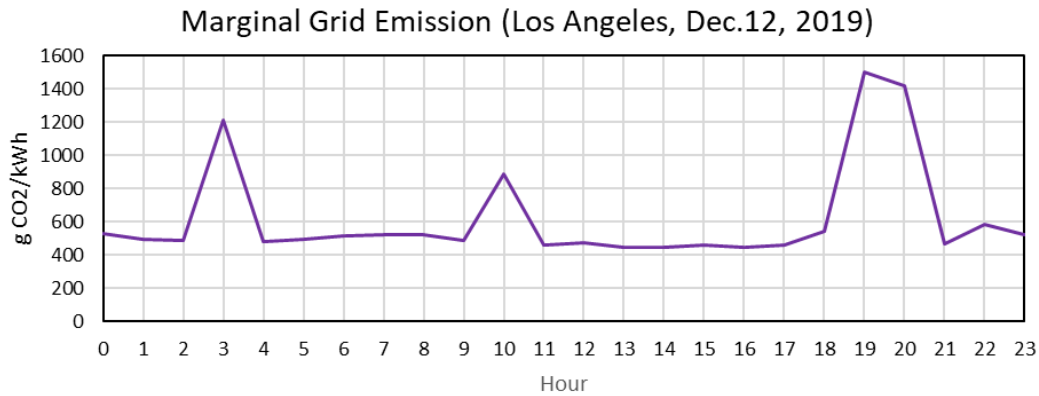


Figure 10: Marginal Grid CO₂ Emission in Los Angeles, Dec. 12th, 2019

The hourly utility cost of SFFHP is shown in Figure 11. In the morning, the operation cost of heating device is generally higher due to the low outdoor temperature as shown in Figure 9. Running the heat pump alone shows the highest cost, and running the furnace alone shows the lowest cost due the significant price difference between electricity and gas. The utility cost of the SFFHP under two control strategies are between the cost of running furnace alone or running heat pump alone.

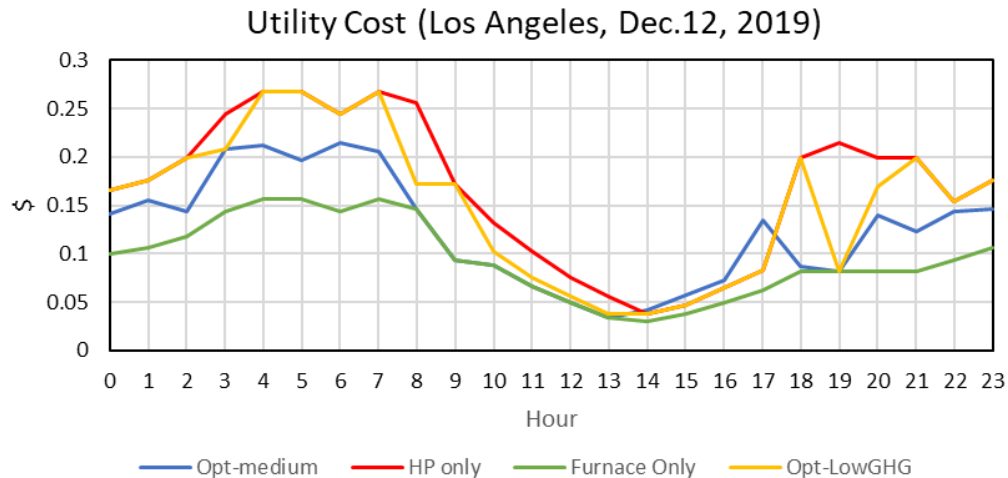


Figure 11: Hourly Operation Cost of SFFHP in Los Angeles, Dec. 12th, 2019

Figure 12 shows the hourly CO₂ emissions of different systems. The Opt-LowGHG operation strategy of SFFHP yields the lowest emission. The peak emission of heat pump matches with the marginal grid emission peaks as seen in Figure 10, since heat pump only consumes electricity. And SFFHP operated under either optimal control strategies can effectively shave the emission peaks by consuming gas during the grid emission-intensive period. This demonstrates the capability of SFFHP for peak demand reduction.

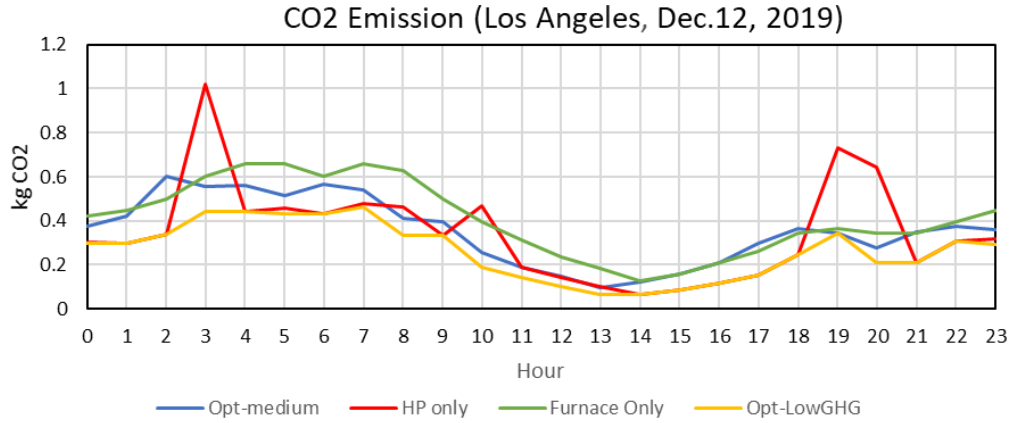


Figure 12: Hourly CO2 Emission in Los Angeles, Dec. 12th, 2019

Figure 13 shows the percentage of heating capacity provided by each subsystem of SFFHP for Opt-LowGHG and Opt-medium operation cases.

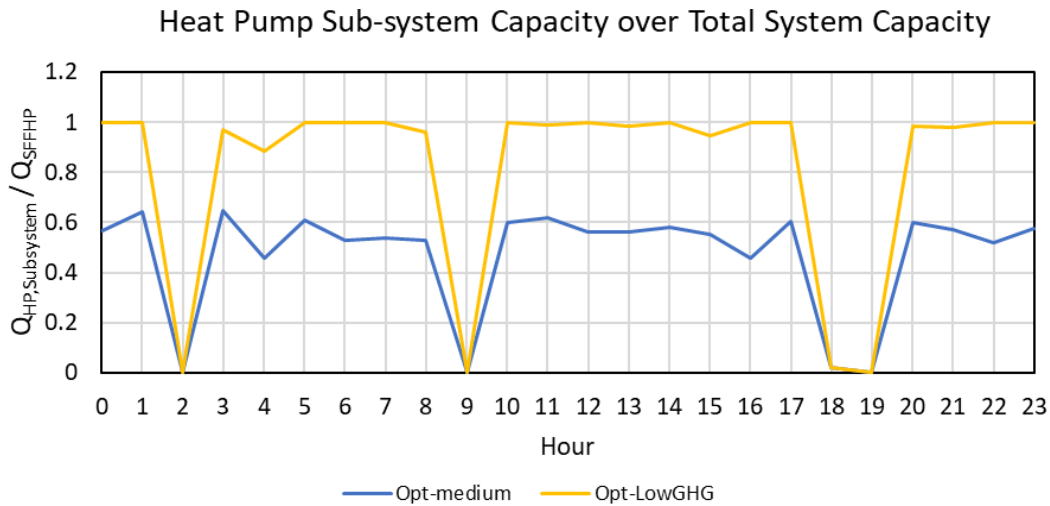


Figure 13: Capacity Ratio between Electric Heat Pump Sub-system to SFFHP System

Chicago case study

The similar case study is performed in Chicago. The TMY-3 weather data from January 1st, 2020, to February 29th, 2020, in Chicago is used. The adopted Time-of-Use utility rate is from ComEd company, and the natural gas price is adopted from Peoples Gas company as indicated in Figure 14.

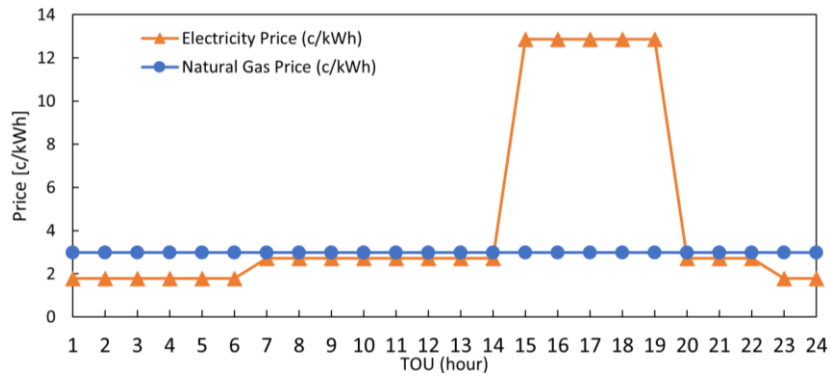


Figure 14: Time-of-Use Utility Rate from ComEd and Gas Price from Chicago in 2020

The performance of SFFHP operated under the optimal control strategies in Chicago is presented in Figure 15. A sampled performance point using the control strategy in the middle of Pareto Fronts yields 49% CO₂ reduction compared to operating furnace alone and 33% utility cost reduction compared to operating heat pump with electric heater as ancillary heating source. As the climate in Chicago is much colder than Los Angeles, SFFHP shows more utility saving benefits in Chicago. In addition, due to the less renewable compositions in the grid of Chicago compared with California, SFFHP shows more emission reduction potentials in Chicago than in Los Angeles.

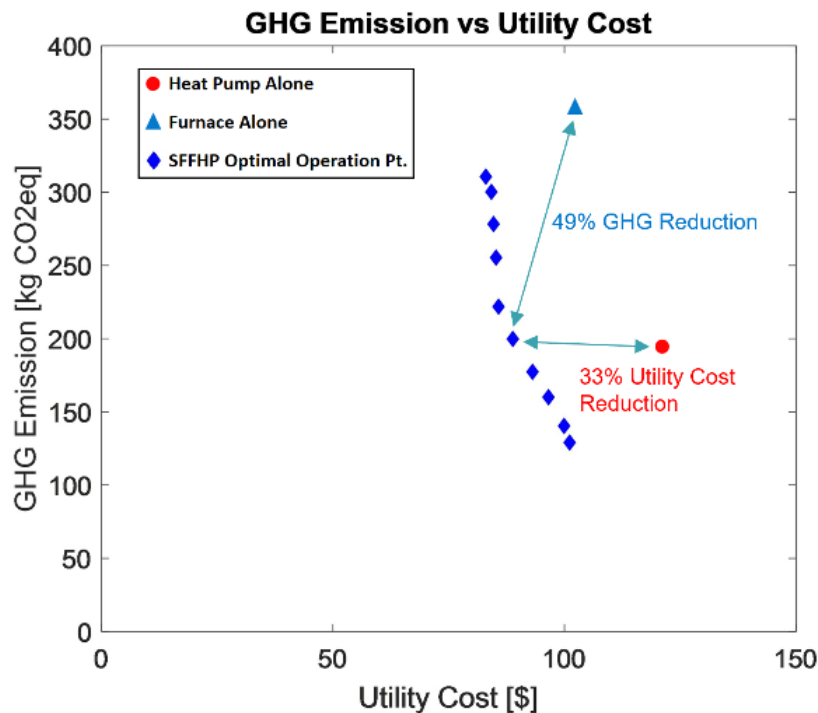


Figure 15: Pareto Front for SFFHP Performance Operated Using the Optimal Control Strategies in Chicago

The Pareto Fronts shows that the performance of SFFHP is superior to the furnace alone or the heat pump alone. Case studies in different regions demonstrate by optimizing the control strategy of SFFHP, significant utility cost saving and GHG emission reduction can be achieved compared with conventional spacing heating systems.

Conclusion

This research introduces a novel hybrid fuel heat pump, the seamlessly fuel flexible heat pump (SFFHP), which simultaneously consumes gas and electricity and continuously optimizes the proportion of each. SFFHP accounts for the balance between economic and environmental impacts of the residential and small commercial space heating equipment.

To regulate the operation of SFFHP, various temporal inputs are used to develop the MPC strategy, including real-time electricity price and gas price, heat pump efficiency, furnace efficiency, and marginal grid emissions. Case studies demonstrate significant reductions in peak demand, utility cost, and CO₂ emissions when operated with optimal control strategy: up to 33% utility cost reduction and 49% CO₂ emission reduction in Chicago, and 23% utility cost reduction and 17% CO₂ emission reduction in Los Angeles. Due to the hybrid fuel nature of this novel equipment, user comfort will always be maintained, making the technology an attractive option for demand response programs.

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