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Enabling Refrigerator Controls to Respond to Hourly Dynamic Electricity Prices

By

ABDULAZIZ N A E ALMESERI
THESIS

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Abstract

This thesis presents a new control system that enables domestic refrigerators to respond to hourly dynamic electricity prices. A dynamic thermal model was developed to simulate the heat exchange behavior, incorporating heat gain through the walls, compressor cooling, automatic defrost, and the effect of thermal mass. The dynamic thermal model characteristics were derived from measurements of a household refrigerator's temperature and power profiles. Based on utility-supplied day-ahead, hourly dynamic prices, the proposed price-responsive mode pre-cools the refrigerator's contents before a peak period and schedules defrost events within a flexible time window, aiming to minimize operating costs through load shifting. To quantify the cost savings, a default mode was developed as a baseline that mimics the physical refrigerator's operation through conventional thermostatic control and fixed defrost events. Using Southern California Edison's hourly dynamic prices, simulation results project monthly cost savings of \$1.2 (8.8%) and 2.5 kWh of load-shifting potential for a single refrigerator. The proposed model can also include the integration of an embedded battery to further reduce costs.

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1. Introduction

Household appliances' control systems are designed to provide a service that meets the comfort and convenience of consumers. Improving the energy efficiency of household appliances has been the center of interest of policymakers, researchers, and manufacturers for decades [1]. These efforts have focused on reducing energy consumption to decrease the stress on the electrical grid without sacrificing the quality of service (QoS) of the appliances. Lowering the energy consumption is not the only approach to reducing grid stress. Load shifting is a technique that shifts the energy consumption from high-usage periods to lower-usage periods, reducing the stress on the grid.

As electrical grids move towards renewable energy, matching load with grid conditions becomes essential due to the intermittent nature of renewable energy. One way to reflect grid conditions on the consumers is to adopt dynamic electricity prices. Different dynamic pricing strategies have been implemented over the years to incentivize consumers to shift/reduce their consumption in high-demand periods. The most dynamic prices are day-ahead hourly dynamic prices, often called real-time prices [2]. Prices are announced a day or less in advance with hourly variations to better represent grid conditions. Hourly dynamic prices must be coupled with autonomous control of household appliances, making them price-responsive to react to the hourly price fluctuations due to the inconvenience of manually adjusting the appliances' operation with highly dynamic prices. Price-responsive control can be achieved through a centralized approach using a home energy management system (HEMS), which is a strategy to coordinate appliances' operation, to optimize consumption [3], [4]. Another approach is a distributed approach, controlling each individual appliance and optimizing its consumption. The distributed approach allows more visibility of each individual appliance's internal operation through sensors, offering more control over the energy consumption and the offered service.

Domestic refrigerators and freezers are responsible for 4% of global electricity consumption from 2 billion units [5]. In the US, 99% of households have at least one refrigerator, and 34% have two or more [6]. These refrigerators account for 7.9% of total residential-sector electricity use [7], [8]. Current refrigerators operate solely on a conventional thermostat control, regardless of whether the refrigerator is full or empty, whether it's day or night, or whether electricity prices are high or low. The shift towards dynamic pricing, driven by higher adoption of renewable energy, necessitates integrating economic factors into a refrigerator's control decisions. The goal is to shift consumption from

on-peak hours to off-peak hours to reduce consumer bills and to support grid resilience. A typical hourly dynamic price has a 3-hour peak period, which means for a single refrigerator, cost and energy savings are expected to be modest. However, at scale, cost savings and load shifting are significant.

2. Literature review

Previous studies have examined modeling household refrigerators and optimizing their energy consumption. The overwhelming majority of studies optimized refrigerators under a time-of-use electricity pricing scenario. In recent years, hourly dynamic prices have been proposed through pilot programs in California [9], [10]. Thus, this study focuses on optimizing refrigerator operation under hourly dynamic pricing to demonstrate the potential cost and energy savings. The first section in the literature review discusses the key factors affecting refrigerator energy consumption. The second section discusses the various approaches used to model a refrigerator. Section three focuses on categorizing optimization control approaches. Section four discusses previous work in refrigerator optimization approaches and results. The last section discusses the time-of-use and hourly dynamic electricity prices.

2.1 Factors Affecting Refrigerator Energy Consumption

Understanding key drivers affecting refrigerator energy consumption is an essential first step towards modeling and optimizing it. Key factors fall into 3 categories: 1) room temperature, 2) user interactions, and 3) automatic defrosts. Harrington et al. found that room temperature is the strongest factor affecting energy consumption, accounting for 75% of energy consumption across the three categories. When the room temperature is high, more heat leaks through the refrigerator walls, and the difference between the condensing and evaporating temperatures increases, reducing refrigeration efficiency. User interactions such as door openings and food loading have a 15% effect on energy consumption. The smallest factor across the three categories is the automatic defrost, which is responsible for 10% of energy consumption [11], [12]. However, automatic defrost is an internal refrigerator mechanism as opposed to the other two categories. Thus, in this project, the first two categories are isolated to focus on the internal refrigerator optimization potential, including automatic defrosts.

2.2 Refrigerator Thermal Modeling

Refrigerator modeling has been studied using various approaches. White-box modeling is a type of modeling that describes all refrigerator components and their relationships using pure physics, without data-driven parameters. There are numerous computational fluid dynamics (CFD) models of refrigerators in the literature [13], [14], [15], [16]. The problem with this type of modeling is that it's computationally heavy and cannot be replicated for other refrigerators due to being unique for a specific refrigerator. In contrast, black-box modeling is a data-driven system with no apparent information to the developer on how the system's interactions occur. Examples include neural networks and fuzzy logic systems where the model gets trained on a large data set to predict future behavior [17], [18], [19]. This type of modeling lacks generalization outside of the training data. Gray-box modeling combines physics principles and empirical data [4], [20], [21], [22], [23]. Resistance-capacitance modeling is a type of gray modeling where the physics of the temperature evolution is based on Newton's law of cooling, while the R and C values are derived from empirical data.

Previous work in gray-box refrigerator modeling used a quasi-steady approach. The refrigeration cycle consisted of four sub-models: compressor, evaporator, condenser, and internal heat exchanger, which were modeled in steady state. Whereas the refrigerator compartments' temperature evolution was modeled in a transient state. The thermostat in the frozen food compartment was responsible for switching the single-speed compressor state. The fresh food compartment temperature was controlled through a thermostatic damper that varied the airflow rate. The authors validated the model with a top-mount frost-free refrigerator, which showed 2% error range in energy consumption and compressor runtime ratio between simulation results and lab-measured data. Additionally, compartment temperature predictions had a maximum deviation of 0.4°C [24].

Aligning with the gray-box modeling used in previous studies, this thesis develops a lumped resistance-capacitance dynamic thermal model to capture the temperature evolution of the refrigerator's air and thermal mass. This framework serves as the foundation for the primary focus of this project: developing a price-responsive algorithm for household refrigerators in hourly dynamic pricing environments.

2.3 Control Strategies

Optimizing refrigerator operation requires choosing a control strategy, either predictive or rule-based. Predictive controls such as model predictive control (MPC) use both the refrigerator model and future electricity prices to find the optimal solution over a window horizon. MPC solves the optimization for a defined window, applies the first command, and re-optimizes. Previous studies have explored MPC control algorithms to optimize a refrigerator's operation [25], [26]. The benefit of MPC is closing the feedback loop, which introduces new updated refrigerator information to the optimization algorithm. However, MPC algorithms are computationally heavy to implement on real-world refrigerator microcontrollers. Additionally, the solution MPC provides is optimal only in the specified window, which may not be the global optimal. A simpler approach, such as rule-based controls, is usually used in a time-of-use setting, due to the nature of fixed on-peak and off-peak hours and prices. The refrigerator pre-cools before peak hours, which results in cost savings [27], [28]. Building on these premises, the proposed algorithm uses a rule-based control coupled with a look-ahead window to pre-cool before a price spike, which can change from day to day in hourly dynamic prices. This methodology is computationally efficient to implement in a real-world refrigerator's control system.

2.4 Optimizing Refrigerator Operation

Controlling temperature setpoints to optimize the refrigerator's energy consumption has been studied in the literature. Previous work explored optimizing refrigerators' temperature setpoints in a nanogrid system with time-varying electricity prices. The nanogrid consisted of a PV panel and a battery, and set a local electricity price based on PV power availability. The optimization framework concentrated energy consumption in daytime when PV power was available. Compared with a constant electricity price (constant temperature setpoint), the framework showed a 21% load shift from nighttime to daytime [27].

Thermal batteries were typically studied through the use of phase change materials (PCMs) that absorb, store, and release thermal energy through changing state from liquid to solid and vice versa. A project explored the use of phase change materials (PCM) as thermal storage for demand flexibility in time-of-use (TOU) rates. Charging the PCM

during off-peak hours and discharging during on-peak hours (4-hour window) resulted in 46.3% load reduction and cost savings [28].

While the integration of PCMs offers substantial cost savings, it requires a physical modification to the refrigerator architecture. A practical alternative method used in this project is to use standard refrigerator contents as a thermal battery. By strategically adjusting the temperature setpoint based on future electricity prices, the system pre-cools the thermal mass contents prior to a peak period. This thermal storage provides the necessary thermal inertia to maintain the refrigerator interior temperature during peak hours without activating the compressor.

2.5 Time-Varying Prices

The electricity retail market offers a variety of rate structures ranging from flat rates to real-time rates. Traditionally, flat rates were the dominant rate structure among customers. As renewable energy integration in the grid increased, time-varying rates have grown in popularity among utilities to incentivize consumers to shift their load to periods of abundant renewable energy availability as large-scale energy storage cannot be justified economically. Time-varying pricing can be categorized into three categories: 1) time-of-use rates, 2) peak day pricing, and 3) real-time pricing. TOU rates divide the day into multiple periods defined as peak and off-peak. Some TOU rates have an additional period defined as a partial peak. Prices are highest in peak periods, then in partial peak periods, and lowest in off-peak periods. In TOU rates, prices don't vary day by day, but they may vary by season. TOU rates offer certainty for customers, incentivizing them to permanently shift their load to off-peak prices. However, TOU doesn't reflect the wholesale market conditions, making the price variability more conservative compared to a more dynamic pricing plan. Peak day pricing is a pricing scheme where customers pay more for a few hours in a small number of days in a year during the highest grid demand, and is usually announced a day in advance, while receiving a discount on electricity usage the rest of the year. High cost savings have been reported through load shifting through this pricing scheme. However, customers found it inconvenient to react to the price spike through a notification system within a short time. Real-time prices are the most dynamic, where prices vary by hour and are announced a day in advance or an hour in advance. These prices are most reflective of wholesale market conditions, but they require automation on the customer side [29], [30], [31].

To the best of our knowledge, no prior work has optimized a refrigerator’s energy consumption using real-world hourly dynamic electricity prices data. Additionally, previous algorithms either focus on optimizing the temperature setpoint or the defrost cycle independently. Addressing these gaps, this thesis proposes a price-responsive mode for household refrigerators through look-ahead, rule-based thermostatic control and a flexible defrost window, using real-world hourly dynamic pricing data.

3. Methodology

3.1 Electricity Prices

Southern California Edison (SCE) has a pilot program that allows consumers to test hourly dynamic pricing [9]. Prices are announced a day in advance, allowing users to schedule their energy usage by shifting their load to cheaper hours. Other utilities such as Pacific Gas & Electric (PG&E), ComEd, and Ameren also offer hourly dynamic pricing for residential customers. In this project, SCE prices from August and December 2025 were used to calculate the electricity cost. Figures 1 and 2 show price samples for a summer day and a winter day.

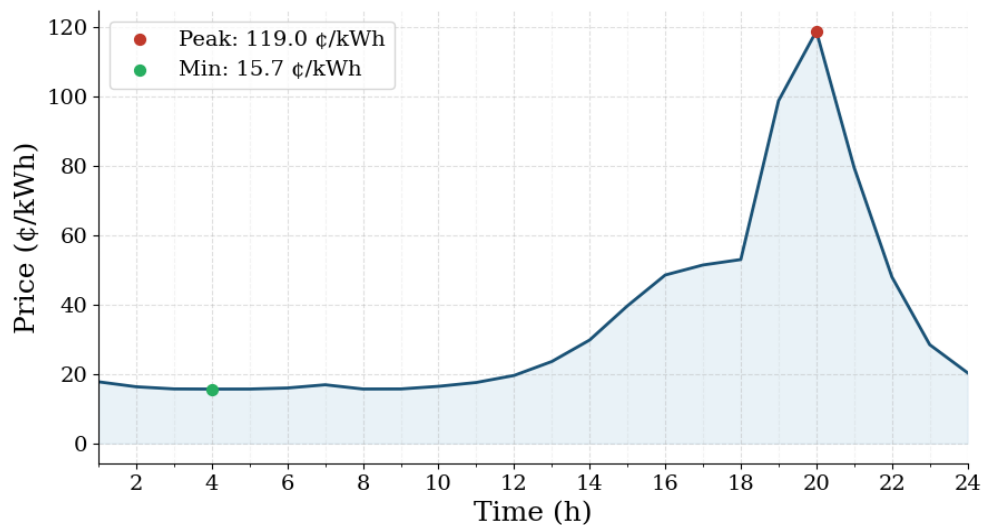


Figure 1: Price sample for a day in August

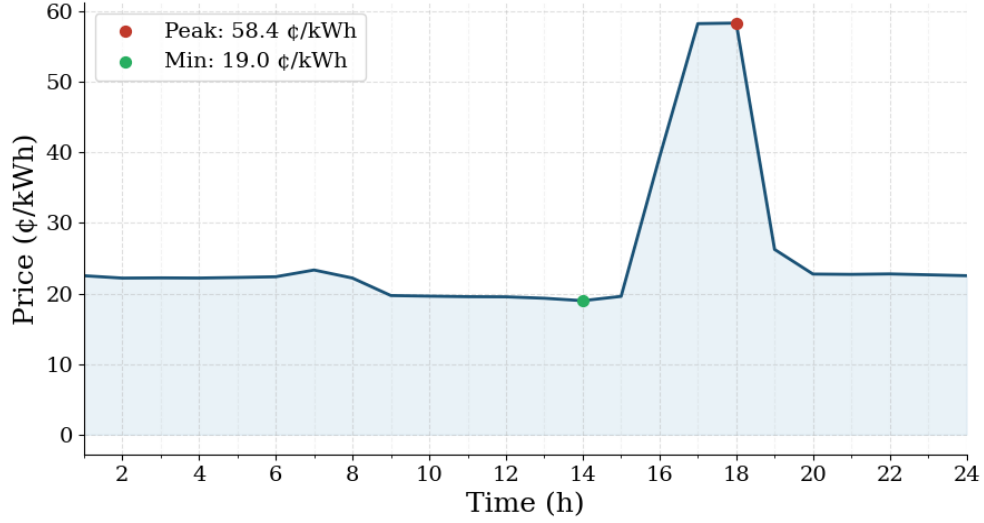


Figure 2: Price sample for a day in December

3.2 Dynamic Thermal Modeling

The refrigerator was modeled as two resistive-capacitive (2R2C) circuits, where the inside of the refrigerator resists the flow of heat from the room through the walls and acts as a capacitor by cooling the system over time and preserving it until heat leaks in [21]. The thermal mass content (water) represents the second resistance-capacitive model, resisting the heat transfer from the refrigerator air and storing cooling energy in the water. The approach followed in this thesis to model a refrigerator was modular, with each refrigerator component having its own module and communicating only heat and electrical power to other modules. Four modules were developed to represent the compressor, the heat-exchange, the automatic defrost, and the thermal mass. The refrigeration cycle that includes the compressor, evaporator, expansion valve, and condenser is collapsed and simplified through the compressor module, which is responsible for providing sufficient cooling power to the refrigerator. The heat-exchange module calculates the amount of heat entering the refrigerator. The automatic defrost module was developed to inject heat into the refrigerator during defrost events. The empirical data showed that defrost events last 30 minutes; during this period, the compressor turns off. In the first 15 minutes, the defrost heater is on, and in the last 15 minutes, the refrigerator does not consume any power (drip time). Most of the heat produced by the defrost heater is used to melt the ice buildup on the evaporator, while a small portion leaks into the refrigerator. Lastly, the thermal mass model was developed to

mimic the food load in a typical refrigerator. These four modules, with their interactions, form the dynamic thermal model as shown in Figure 3.

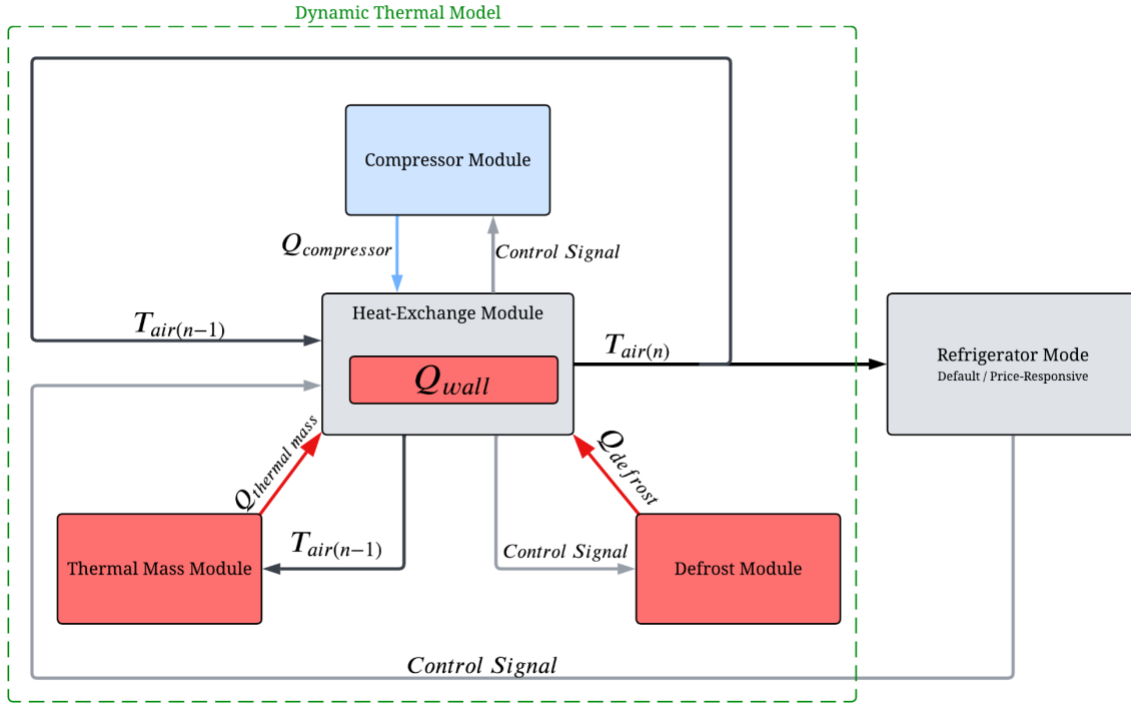


Figure 3: Dynamic thermal model schematic

The refrigerator was modeled as a uniform box having the same temperature throughout its interior. At each time step Δt , the new refrigerator temperature is calculated using equation (1). Temperature evolution equations were linearized to simplify the simulation, as 5-minute time steps provide a sufficient approximation.

$$T_{air(n)} = T_{air(n-1)} + \frac{Q_{net,air} \cdot \Delta t}{C_{refrigerator}} \quad (1)$$

Where:

$T_{air(n)}$ is the refrigerator's interior temperature calculated for the current timestep ($^{\circ}\text{C}$),

$T_{air(n-1)}$ is the refrigerator's interior temperature calculated during the previous timestep ($^{\circ}\text{C}$),

$C_{refrigerator}$ is the experimentally determined thermal mass of the refrigerator ($\text{kWh}/^{\circ}\text{C}$),

$Q_{net,air}$ is the total amount of heat added to the refrigerator (kW), calculated as:

$$Q_{net,air} = Q_{wall} + Q_{defrost} + Q_{thermal\ mass} - Q_{compressor} \quad (2)$$

Where:

$Q_{defrost}$ is the heat added due to defrost (kW),

$Q_{compressor}$ heat removed by the compressor (kW),

Q_{wall} is the conduction heat gain through the walls (kW), calculated using equation 3.

$Q_{thermal\ mass}$ is the heat exchanged between the water and refrigerator air (kW), calculated using equation 4.

$$Q_{wall} = \frac{T_{ambient} - T_{air(n-1)}}{R_{refrigerator}} \quad (3)$$

Where:

$T_{ambient}$ is the room temperature (°C),

$R_{refrigerator}$ is the experimentally determined thermal resistance of the refrigerator walls (°C/kW).

$$Q_{thermal\ mass} = \frac{T_{air(n-1)} - T_{thermal\ mass(n-1)}}{R_{thermal\ mass}} \quad (4)$$

Where:

$T_{thermal\ mass(n-1)}$ is the water temperature calculated for the previous timestep (°C),

$R_{thermal\ mass}$ is the calculated thermal resistance of the water (°C/kW).

The thermal mass temperature is calculated as:

$$T_{thermal\ mass(n)} = T_{thermal\ mass(n-1)} + \frac{Q_{thermal\ mass} \cdot \Delta t}{C_{thermal\ mass}} \quad (5)$$

Where:

$T_{thermal\ mass(n)}$ is the water temperature calculated for the current timestep (°C),

$C_{thermal\ mass}$ is the water thermal mass (kWh/°C).

The energy consumption is calculated in the heat-exchange module sourced from either the defrost module or the compressor module each time step, because during defrost events, the compressor shuts off.

To derive the dynamic thermal model parameters, a temperature sensor was placed inside a household refrigerator to measure the air temperature in real-time. An additional temperature sensor was placed in the room to measure the room temperature. Power consumption was also monitored using an Emporia smart plug. Power consumption and temperature behavior of a GE GTL18JBPFBRBS top-freezer refrigerator were monitored over months where room temperature varied between 18°C to 28°C for both an empty refrigerator and a loaded refrigerator with 20 kg of water bottles. Key modeling parameters derived from lab-measured data are listed in Table 1. Model assumptions are listed in Table 2.

Table 1: Model parameters

Metric	Value	Unit
Thermal Mass, $C_{refrigerator}$	0.017	kWh/°C
Thermal Resistance, $R_{refrigerator}$	140	°C/kW
Compressor Power	150	W
Defrost Power	400	W
Heat Added by Defrost, $Q_{defrost}$	50	W

Table 2: Model assumptions

Metric	Value	Unit
Water load	20	kg
Thermal Resistance of water, $R_{thermal\ mass}$	36.76	°C/kW
COP	2	Unitless
Room Temperature, $T_{ambient}$	23	°C
Simulation time step, Δt	5	minutes

The lab-measured refrigerator temperature versus the modeled refrigerator temperature (using equation 1) is shown in Figure 4. The measured temperature was normalized from 1-minute to 5-minute data points. The figure shows the temperature behavior over ~9 hours; each data point represents a 5-minute time step.

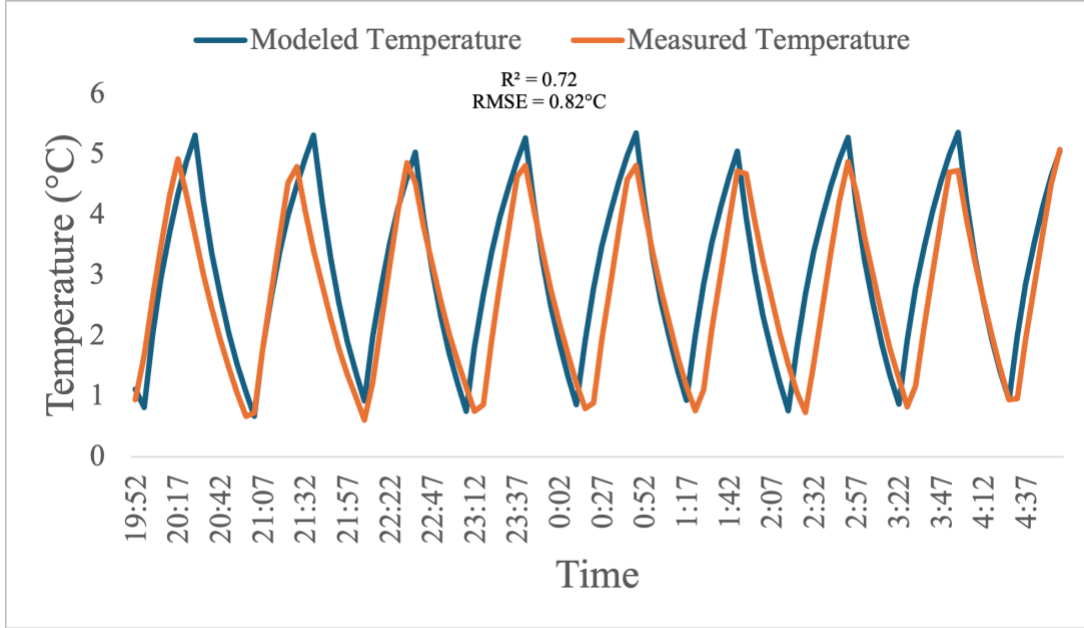


Figure 4: Refrigerator interior temperature profile (modeled vs measured)

3.3 Refrigerator Modes

The refrigerator can operate in either the default mode or the price-responsive mode, with the only difference being the control decisions. The default mode mimics a typical household refrigerator that isn't price-aware and operates solely based on the temperature conditions inside the refrigerator. The price-responsive mode control strategy includes both temperature and electricity prices in the decision-making. Both modes operate on 5-minute time steps; temperature and power consumption get updated every 5 minutes.

The price-responsive mode was developed by controlling the refrigerator's temperature setpoint depending on the price of electricity. The refrigerator's air temperature is constrained by a food-safe range of temperatures ranging from 1°C to 6°C. During off-peak hours (most of the day), the air temperature of the refrigerator is set to a lower limit of 1°C and an upper limit of 5°C. The control system has the ability to look ahead 2.5 hours to determine the peak hour

prices. When it detects a peak period, the temperature setpoint is lowered to force the refrigerator's air temperature to operate between 1°C and 1.5°C, pre-cooling the refrigerator by charging the thermal mass (water). The thermal mass of the stored cold water preserves the cooling thermal capacity until the peak period, when the temperature setpoint is increased to force the refrigerator's air temperature to fluctuate between 5°C and 6°C, allowing the thermal mass to discharge and coast through the peak period. The charging decision is based solely on the price spread ratio; when the price difference is not large enough, pre-cooling will cost the user more than keeping the temperature within the normal range. Through calibration, pre-cooling when the current price is less than 70% of the future price is the most effective ratio for the price data used. The refrigerator exits coast mode and resumes normal operation when the price drops below 70% of the peak price. Figure 5 shows a high-level overview of the price-responsive flowchart.

The other feature that can increase cost savings is the defrost scheduling. The price-responsive mode has a flexible defrost schedule with a maximum window constraint. The duration between two defrost cycles was set to be anytime between 12 to 16 hours. The algorithm will choose the cheapest period to operate a defrost schedule, taking into account the refrigerator temperature recovery period.

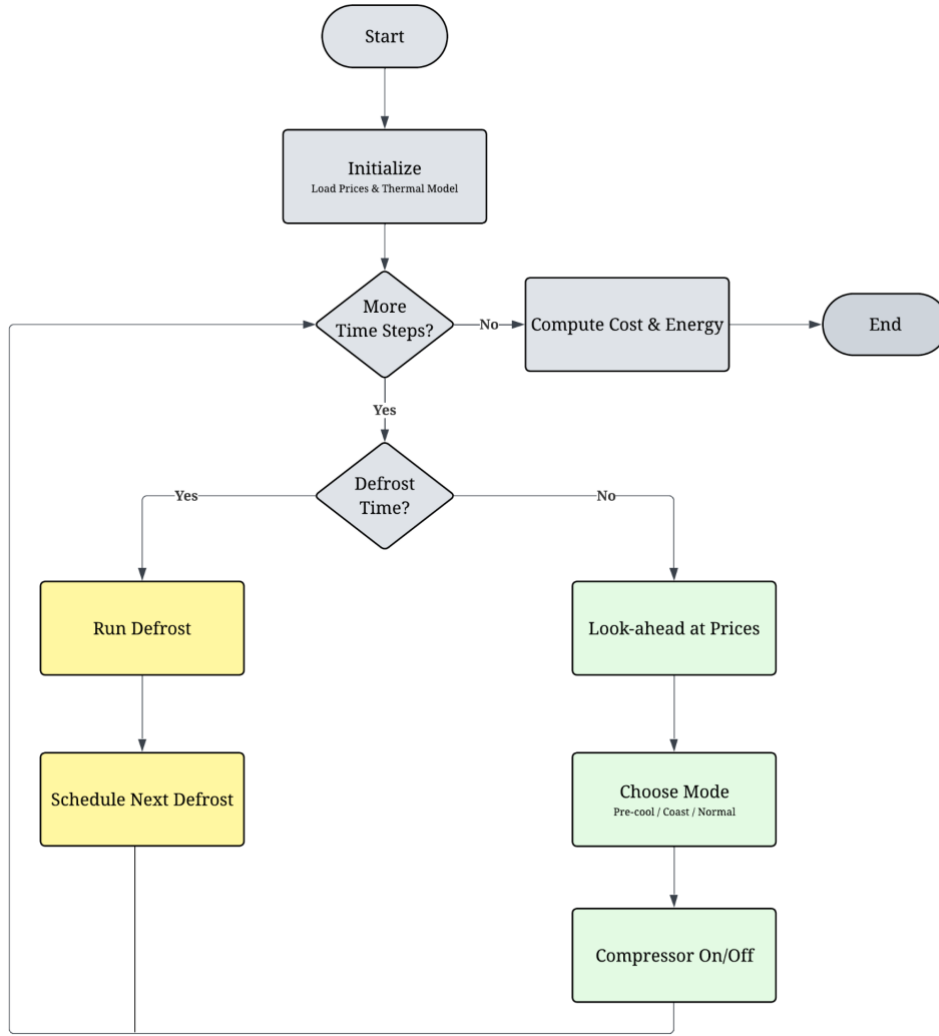


Figure 5: Price-responsive mode flowchart

The default mode was developed to mimic the behavior of the GE GTL18JBPRBS top-freezer refrigerator. The compressor starts when the refrigerator temperature reaches 5°C and shuts down when the refrigerator reaches 1°C. The defrost schedule is hard-coded with 12 hours between each cycle. This mode is the baseline to measure the performance of the price-responsive mode in terms of operational cost.

4. Results and Discussion

Figures 6 and 7 show simulations of the refrigerator in default mode for a day in August and in December. The temperature fluctuates between 1°C and 5°C the entire day. The only exception is the defrost period, during which the

compressor is off while heat is leaking into the refrigerator. The compressor cycle duration is determined by the refrigerator's temperature reaching its limits. On both days, the refrigerator consumed 1.9 kWh at an average temperature of 3.2°C. The cost for one day of operation is \$0.66 in August and \$0.49 in December.

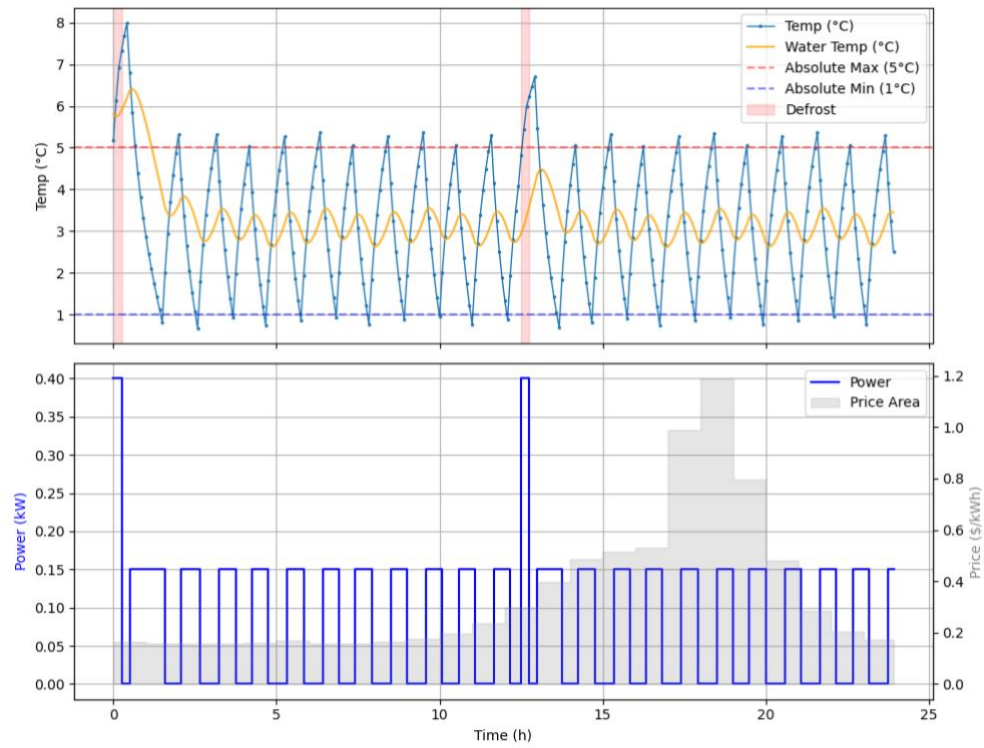


Figure 6: Default mode simulation for a day in August

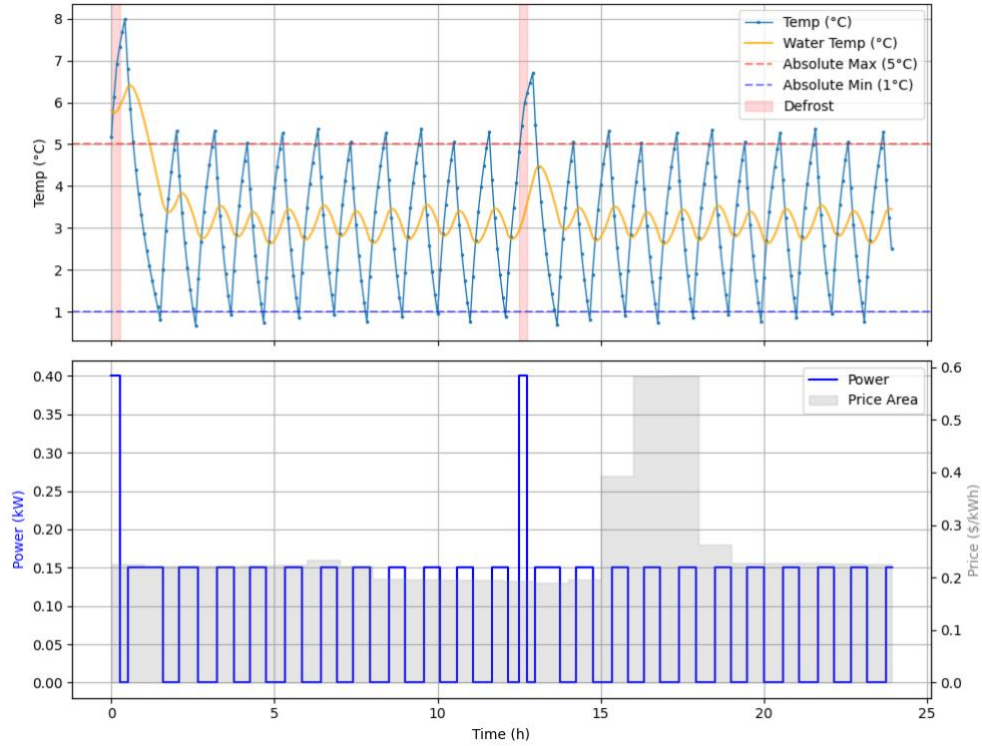


Figure 7: Default mode simulation for a day in December

Figures 8 and 9 show simulations of the refrigerator in price-responsive mode for the same day in August and in December. The temperature fluctuates between 1°C and 5°C throughout the day. The refrigerator detects a peak period 2.5 hours in advance, and it starts pre-cooling to charge the thermal mass (water). When the peak period arrives, the refrigerator can ride through approximately 40 minutes without any power consumption. When the thermal battery is fully discharged, the refrigerator goes into coast mode (temperature fluctuates between 5°C and 6°C) until the price drops below 70% of the peak hour. The defrost is scheduled at the cheapest period in the allowed window (between 12 and 16 hours after the last defrost event). Pre-cooling is independent of the defrost, in figure 8 it shows that the refrigerator pre-cools and then enters a defrost. Pre-cooling can be prevented before a defrost event, but results show that pre-cooling before a defrost can reduce costs when the temperature recovery price period is higher than the period before the defrost event. In a day in August, the refrigerator in price-responsive mode consumed 1.9 kWh at a cost of \$0.62, operating at average temperature of 2.9°C. On a day in December, the refrigerator in price-responsive mode consumed 1.9 kWh and cost \$0.46 with an average temperature of 3.2°C.

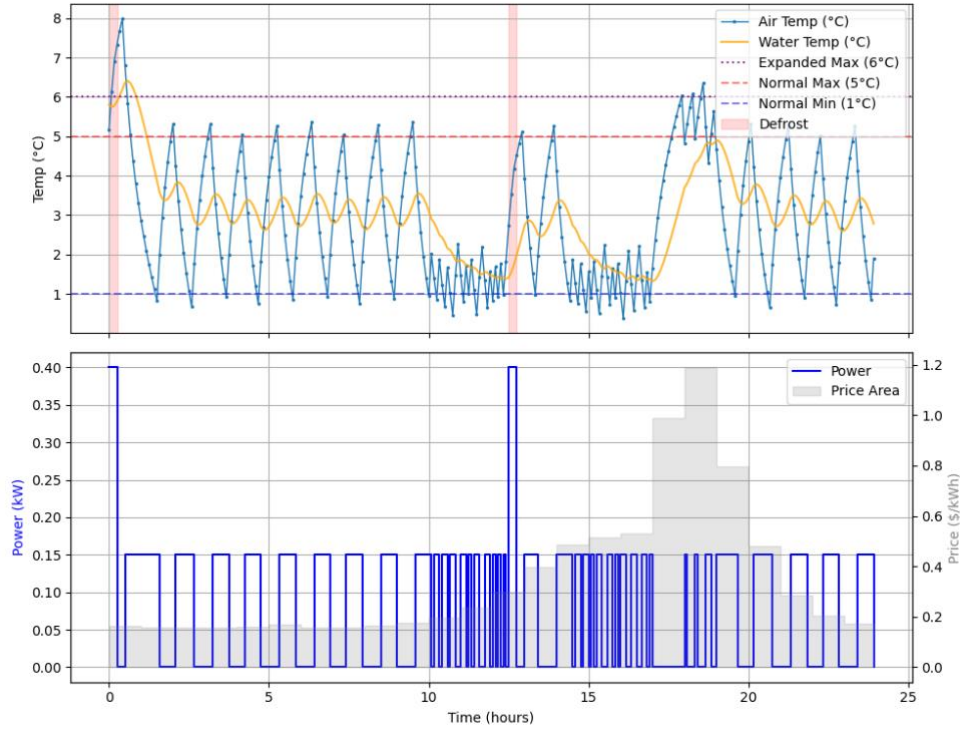


Figure 8: Price-responsive mode simulation for a day in August

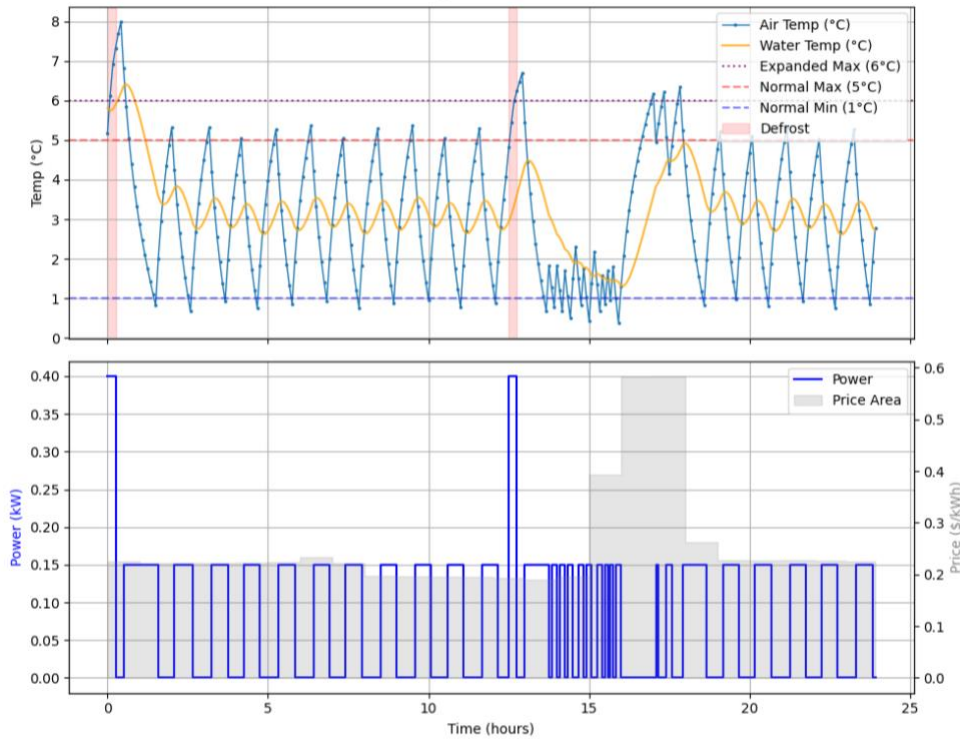


Figure 9: Price-responsive mode simulation for a day in December

To compare the results, the refrigerator was simulated using both modes for the whole months of August and December. The peak period is defined as the prices above the 80th percentile of the whole month. The results are shown in Tables 3 and 4. Compared to the default mode, the price-responsive mode consumes 2 to 2.5 kWh/month less energy during peak hours, of which 1 to 1.5 kWh/month is shifted to off-peak hours, and the rest is saved. Both modes operate at the same average temperature, and cost savings range from \$1 to \$1.2 per month. The trade-off is the wear and tear the compressor experiences due to more cycles in price-responsive mode than in default mode.

Table 3: August results

	Default Mode	Price-Responsive Mode
Total Energy (kWh)	59.3	58.4
Peak Usage (kWh)	11.8 (20%)	9.9 (17%)
Off-Peak (kWh)	47.5 (80%)	48.5 (83%)
Average Temperature (°C)	3.1	3.1
Number of Compressor Cycles	713	987
Total Cost (\$)	12	11

Table 4: December results

	Default Mode	Price-Responsive Mode
Total Energy (kWh)	59.2	58.1
Peak Usage (kWh)	12.1 (20.5%)	9.5 (16.4%)
Off-Peak (kWh)	47.1 (79.5%)	48.6 (83.6%)
Average Temperature (°C)	3.1	3.1
Number of Compressor Cycles	713	937
Total Cost (\$)	13.7	12.5

The simulation results show that for a single refrigerator, an average power of 17.7 W can be saved/shifted during the peak period. With a conservative estimate of the number of household refrigerators in California being 17.36 million

[Appendix A], the available statewide load shifting capability from household refrigerators is 307.3 MW, representing 4.39% of the 7 GW goal of load shifting capability by 2030 set by the California Energy Commission (CEC) [32].

5. Conclusion

This thesis proposes a method for domestic refrigerators to automatically respond to hourly variable electricity prices, reducing operating costs through load shifting. An algorithm has been developed to control the temperature setpoint and defrost schedule based on day-ahead, hourly-varying electricity prices. A dynamic thermal model was developed to simulate the temperature behavior of a typical refrigerator and estimate its energy consumption. The model was calibrated with lab-measured data from a typical refrigerator. The price-responsive mode simulation saved \$1.2 per month, resulting in 8.8% cost reduction. These cost savings were achieved through load shifting up to 2.5 kWh/month. Due to the modest cost savings, we can conclude the following:

- 1) The thermal mass in a refrigerator cannot act as a thermal battery for more than 1 hour during peak periods, especially with the tight refrigerator band (1°C to 5°C).
- 2) Current dynamic prices don't incentivize load shifting because the spread between peak and off-peak periods is small.

6. Future Work

To complete the dynamic thermal model, a freezer module will be added, as it has a wider temperature range, potentially increasing the potential for cost savings. User interactions such as door openings and food loading events will be modeled as disturbances that add heat to the refrigerator. Improvements can be made to the defrost scheduling in the default mode to better align with the lab results. Instead of scheduling a defrost based on elapsed time since the last defrost, scheduling must depend on the compressor run time. These sources of uncertainty may have affected the simulation results.

To validate the results of the proposed price-responsive mode in terms of cost savings and load shifting, it will be tested experimentally. A programmable thermostat will replace the current thermostat in the refrigerator, and it will

be connected to a Raspberry Pi that has access to the price data through the cloud. The defrost timer will be replaced with a solid-state relay (SSR) to trigger the defrost operation in the desired period.

The simulation results showed up to \$1.2 of cost savings and 2.5 kWh of energy shifting in a month. To achieve more cost savings, a small battery will be installed in the refrigerator to enable coasting through a longer duration of peak periods while charging at off-peak periods. Preliminary results show that a 500 Wh battery can increase the cost savings by \$1 per month. The battery can also contribute to the grid by selling electricity during peak hours while serving as backup power in case of a power outage.

The proposed price-responsive algorithm can be applied to other household appliances beyond refrigerators. Thermostatically controlled loads, such as water heaters and HVAC systems, can integrate the price-responsive mode to pre-heat the water or pre-cool the room before peak periods, thereby achieving cost savings through load shifting.

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Appendix A

According to the 2020 residential energy consumption survey (RECS), California had 4.18 million housing units with 2 or more refrigerators out of 13.18 million total occupied housing units [33]. A conservative estimate of the total number of refrigerators is 17.36 million, assuming only 2 per household among the 4.18 million households with multiple refrigerators.