Advanced Predictive Rule-based Control for HVAC Cost Reduction Under Dynamic Electricity Pricing in Residential Buildings

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ABSTRACT

Efficient electrification of space heating/cooling presents the most viable pathway to GHG emissions reduction, and heat pumps (HPs) remain the dominant alternative for replacing gas/oil-based space heating systems. To achieve widespread adoption of HPs, it is imperative to improve their energy efficiency and operational cost. In this paper, a scalable and computationally inexpensive advanced predictive rule-based-control (PRBC) strategy for HPs is presented. The controller is tested on an EnergyPlus prototype model of a single-family detached house within the building optimization testing framework (BOPTEST). The HVAC system consists of a single-speed HP, inclusive of a single-speed DX heating coil, a single-speed DX cooling coil, and a constant-speed fan. The PRBC model uses the current indoor air temperature inside the building, day-ahead ambient air temperature, and hourly electricity price (HEP) forecasts to preheat/precool a building, with the final goal of HVAC cost/energy reduction without a noticeable increase of indoor thermal discomfort. The ambient air temperature and HEP forecasts are integrated into the PRBC model by: (i) assigning proportional weight to the forecasted values, prioritizing closer time steps to the present, due to the intuitive principle that forecasting accuracy diminishes with greater temporal distance from the present, (ii) modulating the amount of precooling/preheating based on weighted ambient air temperature and HEP forecasts to not only shift HVAC energy usage from high to low HEP periods but also avoid excess precooling/preheating. Results show the advanced PRBC of being able to identify and quickly respond to finer trends in HEP and ambient temperature than the other controllers resulting in cost/energy savings. The thermal discomfort of the advanced PRBC is comparable to the other controllers, proving the efficacy of the proposed PRBC in judiciously preheating/precooling the building. The advanced PRBC performs significantly better in the cooling season than the heating season, achieving as high as 14%, 9%, and 8% in monthly cost savings, and 11%, 6%, and 8% in monthly HVAC energy savings, as compared to the industry standard, relaxed baseline and literature inspired controllers respectively.

1. INTRODUCTION

1.1 Motivation and Literature Review

Buildings account for about 30% of the global final energy consumption and 26% of global energy related emissions (International Energy Agency, 2024). In order to meet satisfactory indoor air environment (i.e, thermal comfort), more than 50% of a residential building's energy need is spent on heating, ventilation and air-conditioning (HVAC) (United States Environmental Protection Agency, 2009), leading to considerable greenhouse (GHG) gas emissions for HVAC systems that consume fossil fuels onsite. Efficient electrification of space heating/cooling presents the most viable pathway to GHG emissions reduction, and heat pumps (HPs) remain the dominant alternative for replacing gas/oil-based space heating systems. The indoor air temperature is a major determining factor in the HVAC energy usage/costs of a building (Alimohammadisagvand, Jokisalo, & Sirén, 2018). One of the most popular techniques for HVAC load shifting is to precool or preheat the building before peak price periods, while maintaining indoor thermal comfort. Precooling or preheating the building uses the thermal mass of the building to store thermal energy during low price periods which can be released to maintain the indoor air temperature within the acceptable thermal comfort bounds, even obviating HVAC equipment usage during the high price periods, thereby saving electricity costs.

Model predictive control (MPC) based HVAC system controllers can be effectively used to exploit the thermal mass of a building in reducing/shifting HVAC costs and energy. However, an MPC based HVAC controller requires a lower order model for the system to be controlled, which increases computational complexity on top of being tedious to model (Clauß, Stinner, Sartori, & Georges, 2019). Moreover, Goyal, Ingley, and Barooah (2013); Goyal, Barooah, and Middelkoop (2015) showed that well designed rule based controllers (RBC) are as effective as MPC based controllers, defeating the purpose of the added complexity in the MPC. Data driven Machine Learning (ML) based controllers can simplify the modeling complexity of the MPC, but suffers from the requirement of high quality training data, which reduces scalablity (Stoffel, Maier, Kümpel, Schreiber, & Müller, 2023). Instead, predictive rule based controllers (PRBC) can be used to reduce/shift the HVAC cost/load with simpler, highly interpretable and computationally inexpensive implementation, and can still be effective. Thus, we limit our discussion to studies on rule based control (RBC) methods, with a specific focus on predictive RBC (PRBC) methods, to provide guidelines in choosing an appropriate control scheme that strikes a balance between computational complexity and benefit in the form of HVAC cost and energy savings. PRBC methods differ from non-predictive RBC in considering predictions about weather, hourly electricity price (HEP) etc., rather than being completely momentary (Gwerder, M., Tödtli, J. and Gyalistras, D., 2010).

In PRBC, based on the forecasts, for example of HEP, simple pre-decided rules are implemented, which can take the form of setting different temperature setpoints for the building directly (Alimohammadisagvand et al., 2017), or heat pump (HP) ON/OFF signals (Clauß et al., 2019), or both (Alimohammadisagvand et al., 2018). Alimohammadisagvand et al. (2018), presented improvements of two DR based control algorithms already published in their earlier works (Alimohammadisagvand, Jokisalo, Kilpeläinen, Ali, & Sirén, 2016; Alimohammadisagvand et al., 2017) of a combined water based space heating (SH) and domestic hot water (DHW) system. Alimohammadisagvand et al. (2016, 2017) calculated the future HEP trend by the blocking maximum subarray method (which calculates the largest sum of a contiguous subarray within the HEP forecast array), while (Alimohammadisagvand et al., 2018) implemented the more dynamic sliding maximum subarray (which is updated more frequently than blocking maximum subarray method), and moving average algorithm to control the HP and temperature setpoint signals. The sliding maximum subarray method outperformed as compared to the other existing control methodologies with respect to heating cost savings.

Clauß et al. (2019) controlled the HP ON/OFF signals of an air-source HP connected to a water storage tank for both SH and DHW requirements. The authors used different temperature setpoint references at different levels (height) of the water storage tank to ascertain the HP ON/OFF decision signals. The reference temperatures are varied according to the day-ahead HEP by ascertaining three HEP regions - below low price threshold, higher than high price threshold and in between. Additionally, the increasing/decreasing trend of HEP is ascertained in a sliding-horizon method for a 2 hour horizon and is taken into account for setting the reference temperature setpoints. Results showed the method only saves costs in markets where there is a high fluctuation in HEP, whereas in markets where there are marginal fluctuations of HEP, there is a net increase in heating energy imports which outweighed the cost savings due to heating action shift from high to low price periods. Lu, Fu, and O'Neill (2023) compared the rule-based ASHRAE Guideline 36 (GDL36) based HVAC controller with an intelligent optimization based controller (OBC) and a deep reinforcement learning (DRL) based controller for a five-zone variable air volume (VAV) cooling system virtual testbed. Results showed the rule based method to have similar energy performance under both high and mild cooling seasons as compared to the DRL, while having comparable and slightly worse energy performance under high and mild cooling load respectively as compared to the OBC. Goyal et al. (2013) carried out simulations and verified them through experiments in (Goyal et al., 2015) which showed that occupancy and temperature feedback based PRBC can reduce HVAC energy usage as effectively as MPC based strategies without any reduction in thermal comfort or indoor air quality.

An important limitation of (Alimohammadisagvand et al., 2018; Clauß et al., 2019; Alimohammadisagvand et al., 2017, 2016; Lu et al., 2023) is the applicability of each RBC based method either during heating or cooling season, which affects its implementation year around for climatic zones which has both heating and cooling seasons. In addition (Lu et al., 2023; Goyal et al., 2013, 2015) only considered energy savings without consideration for costs which is the primary motivation for consumers to participate in DR. A criticism of RBC based methods used in practice, highlighted by Wang, Tang, and Song (2022) for precooling operation states that, such methods do not effectively adapt to changing conditions, and vary slightly as to when and how much precooling takes place during low price periods to take complete advantage of variable HEP to reduce costs, as compared to a baseline (no precooling) strategy. Additionally, (Wang et al., 2022) critiques that most of the existing RBC methods for reducing on-peak HVAC equipment operation, use time-of-day schedule to reset the indoor air temperature set point when time-of-use (TOU) rate is in place, which hinders efficient adaptation of the RBC methods to electricity markets which vary more dynamically.

1.2 Objective of the work and novelty

The present work develops a advanced PRBC for HP applications in residential buildings under highly dynamic electricity pricing to reduce HVAC electricity costs/energy. The advanced PRBC uses the current indoor air temperature inside the conditioned space, and day ahead predictions of HEP and ambient temperature to determine the preheating or precooling actions to reduce HVAC costs without noticeable increase of indoor thermal discomfort with respect to the predefined ideal range of indoor air temperature. The novelty of the proposed advanced PRBC is as follows:

- A computationally inexpensive yet novel methodology that incorporates future trend in HEP and ambient temperature is presented. The proposed method assigns proportional weight to forecasted values, prioritizing closer time steps to the present, due to the intuitive principle that forecasting accuracy diminishes with greater temporal distance from the present. To the best of the authors' knowledge such a methodology has never been used before in the context of rule-based control.
- By utilizing weighted ambient air temperature forecast in addition to HEP, the proposed preheating/precooling strategy enables efficient shifting of energy use from high to low HEP periods and prevents unnecessary overcooling/overheating, even during low HEP periods, a problem that has nullified PRBC benefits in the past literature (Clauß et al., 2019).
- The adaptability of the advanced RBC is improved over literature, as the same control framework can be applied for both the cooling and heating seasons.
- Consideration of not only HVAC energy but also costs, which is the primary incentive for consumers to participate in DR.

2. RESIDENTIAL BUILDING HEAT PUMP VIRTUAL TESTBED

In this research, the EnergyPlus prototype model of a single-family detached house in a new residential construction was leveraged, aligned with the 2021 version of the International Energy Conservation Code (IECC) (Mendon & Taylor, 2014). We based our study on the Pasco-TriCities TMY3 weather data, specific to Climate 5A. The EnergyPlus model was then reformulated into the Spawn-of-EnergyPlus (Spawn) model (Wetter, Benne, & Ravache, 2021). In this process, HVAC and control elements from the original EnergyPlus model were swapped out for ones based on the Spawn framework in Modelica. The Spawn framework allows for accurate modeling of control sequences and equipment behavior, which is crucial for this research. This Spawn model was compiled into functional mockup units (FMUs) and executed within the Building optimization testing framework (BOPTEST) (Blum et al., 2021), a platform designed for testing, and benchmarking building control algorithms. Within the BOPTEST framework, external signals could override either the heating/cooling temperature setpoints or the HP signal, which we leverage for implementing our control algorithms via Python. The residential HVAC system is a single-speed heat pump, comprising of a single-speed DX heating coil, a supplementary electric resistance heating coil, a single-speed DX cooling coil, and a constant speed fan. The HP's rated Coefficient of Performance (COP) is 3 for cooling and 2.75 for heating.

3. HVAC CONTROL ALGORITHMS

3.1 Overview of controllers and conditions for thermal comfort

The baseline and literature inspired controllers are based on controlling the indoor air temperature setpoints directly, while the proposed PRBC based method is based on directly controlling the HP ON/OFF signal. For acceptable indoor thermal comfort, the minimum and maximum predicted mean vote (PMV) value of −0.5 and 0.5 respectively is chosen, based on ASHRAE Standard 55 (2020). Alimohammadisagvand et al. (2017) formulated linear relationships between maximum and minimum PMV and indoor air temperature ($T_{a,ind}$), given in equation (1), which is used to derive the acceptable range of indoor air temperature.

$$\mathrm{PMV}_{\mathrm{max}} = 0.205 T_{a,\mathrm{ind}} - 4.51, \quad \mathrm{PMV}_{\mathrm{min}} = 0.205 T_{a,\mathrm{ind}} - 4.91. \tag{1}$$

The acceptable range of indoor air temperature is found to be between $T_{\mathrm{comfort,lower}}$ and $T_{\mathrm{comfort,upper}}$ of 21.5 °C and 24.5 °C respectively from equation (1). The temperature deadband (T_{db}) for the controllers described in Section 3.2 and 3.3 (baseline and literature inspired controllers) is 0.5 °C. The temperature deadband for the controllers help avoid rapid cycling of the HP which adversely affects HP lifespan in addition to causing noise pollution, disturbing the user. In Section 3.4 (proposed controller), the HP ON/OFF signal is controlled directly, and rapid cycling of the HP is avoided by persisting with previous control signals which indirectly mimics a situation similar to having a deadband of T_{db} for a fair comparison with controllers in Section 3.2 and 3.3. In this study, we ensured that the HP does not simultaneously operate in both heating and cooling mode within a specific season. The discouragement for the HP to switch between heating and cooling mode intra-season is to ensure lifespan longevity of the HP. However, the control framework in itself does not prohibit switching between heating and cooling modes, and the user might choose it for more operational flexibility.

3.2 Baseline controllers: Fixed indoor air temperature setpoint control

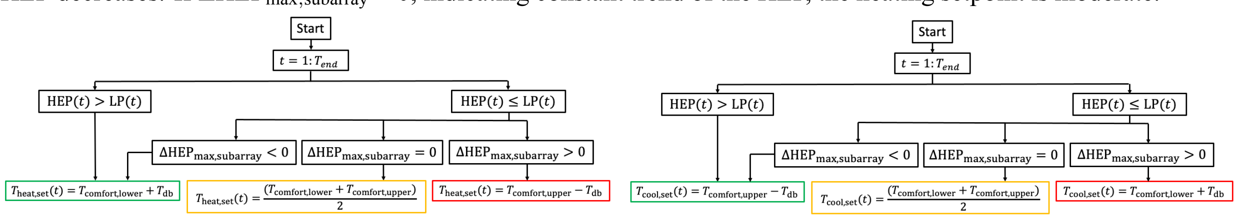
Two fixed baseline indoor air temperature set-point controllers are devised, with only one of the heating or cooling set points applied at a time to avoid intra season HP switching between heating/cooling modes. **Baseline controller (A)** is the industry standard baseline controller which aims to maintain the indoor air temperature at the average of upper and lower comfort limits given in equation (2). The controller starts heating/cooling once the indoor air temperature drops/rises below/above the setpoint. **Baseline controller (B)** is the relaxed baseline controller which permits the indoor air temperature to deviate further from the average setpoint before heating or cooling begins, while still remaining within the thermal comfort bounds. The setpoints for the **Baseline controller (B)** are given in equation (3).

$$T_{\text{heat,set}} = T_{\text{cool,set}} = \frac{T_{\text{comfort,lower}} + T_{\text{comfort,upper}}}{2}. \tag{2}$$

$$T_{\text{heat,set}} = T_{\text{comfort,lower}} + T_{\text{db}}, \quad T_{\text{cool,set}} = T_{\text{comfort,upper}} - T_{\text{db}}. \tag{3}$$

3.3 Literature inspired controller

The literature inspired controller is a PRBC control algorithm based on the sliding maximum subarray problem described in (Alimohammadisagvand et al., 2018, Section 4.2.2). The model uses the current HEP and trend of future HEP to determine the decision and extent of preheating and precooling in the heating and cooling seasons respectively. The flowchart for the literature inspired control algorithm during the heating season is given in Fig. 1a. First, the current HEP is compared to a threshold limiting price (LP). The LP is set as the daily median HEP for the heating season. The daily median HEP can be set at the start of the simulation of each day as it is quite common for electricity markets to announce prices day ahead (Alimohammadisagvand et al., 2018). The model only considers preheating if the HEP is below the LP, to avoid unnecessary preheating costs during high HEP times. The heating setpoint is decided depending on the trend of the HEP in the forecast horizon (considered 5 h in this study). The rising/falling/constant trend of the HEP is decided from the sliding horizon maximum subarray problem, which calculates the increase/decrease/leveling out of the largest sum of a contiguous subarray of HEP forecast in the forecast horizon window. The trend of HEP between two adjacent horizons is thus dependent on only the first HEP entry from the first horizon, which is replaced by the last HEP entry of the second horizon (as the HEP entries in between are still the same), which makes the method in (Alimohammadisagvand et al., 2018) blind to finer trends in HEP. In the present case, as HEP entries are positive numbers, the sliding maximum subarray sum is simply the sum of all the HEP entries in the forecast horizon window. If the trend of HEP increases ($\Delta\text{HEP}_{\text{max,subarray}} > 0$), the heating setpoint is set high to preheat more - as future HEP will increase, leading to increasing HVAC costs if heating is delayed. Similarly, if the trend of HEP decreases ($\Delta\text{HEP}_{\text{max,subarray}} < 0$), the heating setpoint is set low (discouraging heating), as it is economical to heat later when HEP decreases. If $\Delta\text{HEP}_{\text{max,subarray}} = 0$, indicating constant trend of the HEP, the heating setpoint is moderate.



(a) **(b)**

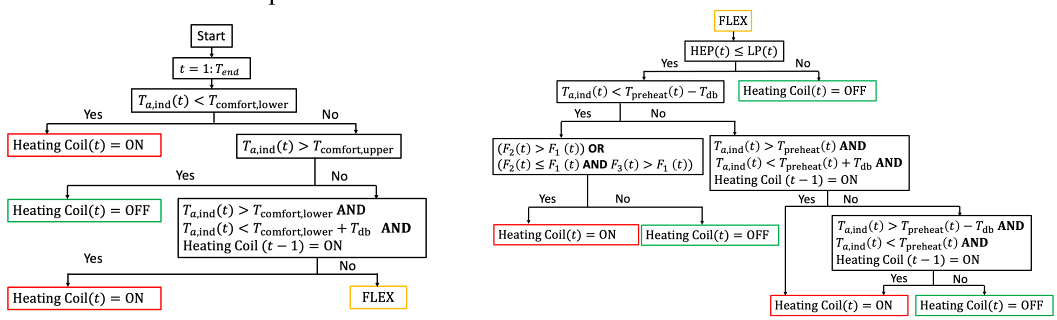
Figure 1: Literature inspired controller flowchart for the (a) heating season, (b) cooling season

The flowchart for the literature inspired algorithm during cooling season is given in Fig. 1b, and follows the same control framework as for heating season, with the LP set as the daily 75$^{\text{th}}$ percentile HEP.

3.4 Proposed controller

The proposed control algorithm directly controls the HP ON/OFF signals, as opposed to setting the indoor air heating and cooling setpoints as in Sections 3.2 and 3.3. The convention of time t followed for this controller is such that HP action at time $(t-1)$ causes a observable change in $T_{a,ind}$ at time t. The flowchart for the proposed control algorithm during the heating season is given in Fig. 2. The Cooling Coil signal is always OFF during the heating season, while the Heating Coil is always OFF during the cooling season.

Figure 2a shows the first control layer, where, depending on the indoor air temperature, and the Heating Coil signal from the last time step, it is decided whereas the controller should go into FLEX mode. Being in FLEX mode is the first check for considering preheating. The goal is to preheat the room during low HEP times to avoid HP usage during high HEP times (i.e., flexibly shifting HP energy usage). If the indoor air temperature is in the thermal comfort zone (i.e., between $T_{\text{comfort,lower}}$ and $T_{\text{comfort,upper}}$), the controller can go into FLEX mode except when indoor air temperature is between $T_{\text{comfort,lower}}$ and $T_{\text{comfort,lower}} + T_{\text{db}}$ and Heating Coil $(t-1)$ = ON. Persisting with the heating at time t when the Heating Coil $(t-1)$ = ON, and the indoor air temperature is between $T_{\text{comfort,lower}}$ and $T_{\text{comfort,lower}} + T_{\text{db}}$, is an indirect way of mimicking the controller to respond similar to literature/baseline with a deadband on heating setpoint. The same method of checking Heating Coil signal at the previous time step is also followed in the FLEX mode of the proposed controller for a fair comparison with literature/baseline controllers.



(a) **(b)**

Figure 2: Proposed control flowchart for the heating season with the (a) primary, and (b) FLEX control layers.

Once the controller is in FLEX mode, Fig. 2b shows that, similar to literature, it is first checked whether HEP is below the LP, to consider preheating. The rationale behind preheating (even when the room air temperature is in the thermal comfort zone) is to increase the indoor air temperature when the HEP is low (but has an increasing trend), resulting in thermal energy being stored in the indoor air. The stored thermal energy can be released during high HEP times, to keep the indoor air temperature comfortable even when the HP is turned off. Note that the LP is same for proposed and literature inspired controller (median daily HEP for heating season). Next, it is checked whether the indoor air temperature is below the preheat temperature setpoint $T_{\text{preheat}}(t)$ with consideration of deadband (T_{db}). The current preheat temperature is decided based on the weighted ambient temperature ($T_{a,\text{amb},W}$) and price (HEP$_W$) forecasts over the 5 h ahead forecast horizon window. The 5 h forecast window is evenly divided into N discrete time steps, with the time index being denoted by k. With the intuitive assumption that near-future forecasts will be more accurate than distant-future forecasts, the weighing factors (W_k) are formulated as

$$W_k \propto 1/k \Longrightarrow W_k = p/k, \quad \forall k = \{1, 2, 3, \ldots, N\} \tag{4a}$$

Also the weighing factors sum upto 1, implying

$$\sum_{k=1}^{N} W_k = 1, \tag{4b}$$

Putting Eqs. 4a and 4b together, the constant of proportionality p is formulated as

$$p = \frac{1}{1 + \frac{1}{2} + \frac{1}{3} + \ldots \frac{1}{N}}. \tag{4c}$$

The weighted ambient temperature and price forecasts are formulated as

$$T_{a,\text{amb},W}(t) = \sum_{k=1}^{N} T_{a,\text{amb}}(t+k \mid t) W_k, \tag{5a}$$

$$\text{HEP}_W(t) = \sum_{k=1}^{N} \text{HEP}(t+k \mid t) W_k. \tag{5b}$$

The current preheat temperature is formulated with $\text{HEP}_{\text{HT}} = \text{percentile}(\text{HEP}_{\text{daily}}, 25)$ as

$$T_{\text{preheat}}(t) = \begin{cases} T_{\text{comfort,upper}} - T_{\text{db}}, & \text{if} \quad \text{HEP}_W(t) \leq \text{HEP}_{\text{HT}} \textbf{ AND } T_{a,\text{amb},W}(t) \leq 5°\text{C} \\ \frac{T_{\text{comfort,lower}} + T_{\text{comfort,upper}}}{2}, & \text{if} \quad \text{HEP}_W(t) \leq \text{HEP}_{\text{HT}} \textbf{ AND } 5°\text{C} < T_{a,\text{amb},W}(t) \leq 10°\text{C} \quad \textbf{OR} \\ & \quad\quad \text{HEP}_W(t) > \text{HEP}_{\text{HT}} \textbf{ AND } T_{a,\text{amb},W}(t) \leq 5°\text{C} \\ T_{\text{comfort,lower}} + T_{\text{db}}, & \text{if} \quad \text{HEP}_W(t) \leq \text{HEP}_{\text{HT}} \textbf{ AND } T_{a,\text{amb},W}(t) > 10°\text{C} \quad \textbf{OR} \\ & \quad\quad \text{HEP}_W(t) > \text{HEP}_{\text{HT}} \textbf{ AND } T_{a,\text{amb},W}(t) > 5°\text{C} \end{cases} \tag{6}$$

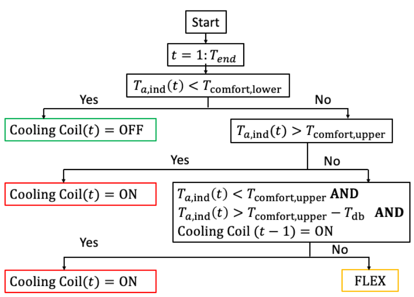
Equation (6) shows that if the HEP$_W$ is low, the T_{preheat} is set higher (for the same $T_{a,\text{amb},W}$) to take advantage of preheating the room during low HEP. The T_{preheat} is set lower for higher $T_{a,\text{amb},W}$ to avoid unnecessary preheating costs as the higher ambient air temperature can in itself increase the indoor air temperature. T_{preheat} is set considering a trade off between taking advantage of low HEP periods without over heating, as PRBC studies in the past have encountered problems of the energy savings due to load shifting from high to low HEP periods being outweighed by increase in electricity use due to overheating leading to increasing HVAC costs (Clauß et al., 2019).

In order to incorporate the trend of the HEP (F), the 5 h ahead forecast horizon is divided evenly into 3 sub-horizons, of 3 h each. The first, second and third sub-horizons cover hours 0 – 3, 1 – 4 and 2 – 5 respectively. Each sub-horizon is evenly divided into n discrete time steps, with each time step covering $3/n$ hours, being indexed by k. With the same intuitive assumption as near-future forecasts being more accurate than distant-future forecasts, we define the 3h subhorizon weighting factors as $w_k = q/k,\ \forall k = \{1, 2, 3, \ldots, n\}$, where $q = \frac{1}{1+\frac{1}{2}+\frac{1}{3}+\ldots\frac{1}{n}}$. The weighted HEP over the first (F_1), second (F_2), and third (F_3) sub-horizons are defined as

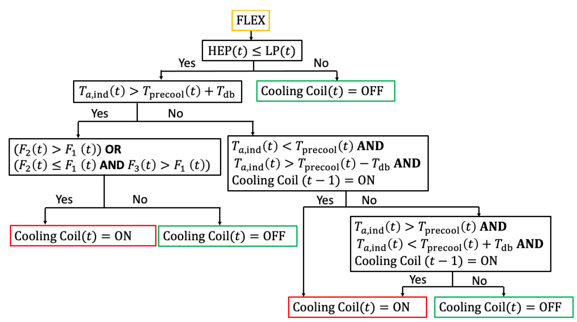
$$F_h(t) = \sum_{k=j+1}^{n+j} \mathrm{HEP}(t+k \mid t) w_{k-j}, \quad h = \{1, 2, 3\}, \quad j = \frac{n(h-1)}{3}. \tag{7}$$

Dividing the 5 h horizon into 3 sub-horizons is able to capture finer trends of HEP, contrary to the literature inspired controller which is unable to see finer trends of HEP. If the indoor air temperature is below the preheat temperature setpoint with consideration of deadband, the trend of the HEP is checked by comparing F_1 with F_2, and F_1 with F_3. An immediately increasing HEP ($F_2 > F_1$) or a momentarily decreasing/leveled out HEP ($F_2 \le F_1$) followed by a major increase of HEP ($F_3 > F_1$) warrants preheating to be done now to avoid future high HVAC costs if heating is delayed. A decreasing HEP ($F_2 \le F_1$ **AND** $F_3 < F_1$) turns off the HP, as it is more economical to heat later when HEP reduces. The two remaining control conditions in Fig. 2b makes sure that the proposed controller incorporates the deadband consistent with literature/baseline.

The flowchart for the proposed control algorithm during the cooling season is given in Fig. 3. The algorithmic framework for the proposed controller during cooling season is same as that of the heating season, with preheating being replaced by precooling. Note that the LP is set as the daily 75$^{\text{th}}$ percentile HEP for the cooling season, similar to the literature inspired controller.



(a)



(b)

Figure 3: Proposed control flowchart for the cooling season with the (a) primary, and (b) FLEX control layers.

The current precool temperature is formulated with $\mathrm{HEP}_{\mathrm{CT}} = \mathrm{percentile}(\mathrm{HEP}_{\mathrm{daily}}, 50)$ as

$$T_{\mathrm{precool}}(t) = \begin{cases} T_{\mathrm{comfort,lower}} + T_{\mathrm{db}}, & \text{if} \quad \mathrm{HEP}_W(t) \le \mathrm{HEP}_{\mathrm{CT}} \ \textbf{AND} \ T_{a,\mathrm{amb},W}(t) \ge 20°\mathrm{C} \\ \frac{T_{\mathrm{comfort,lower}} + T_{\mathrm{comfort,upper}}}{2}, & \text{if} \quad \mathrm{HEP}_W(t) \le \mathrm{HEP}_{\mathrm{CT}} \ \textbf{AND} \ 10°\mathrm{C} \le T_{a,\mathrm{amb},W}(t) < 20°\mathrm{C} \quad \textbf{OR} \\ & \qquad \mathrm{HEP}_W(t) > \mathrm{HEP}_{\mathrm{CT}} \ \textbf{AND} \ T_{a,\mathrm{amb},W}(t) \ge 20°\mathrm{C} \\ T_{\mathrm{comfort,upper}} - T_{\mathrm{db}}, & \text{if} \quad \mathrm{HEP}_W(t) \le \mathrm{HEP}_{\mathrm{CT}} \ \textbf{AND} \ T_{a,\mathrm{amb},W}(t) < 10°\mathrm{C} \quad \textbf{OR} \\ & \qquad \mathrm{HEP}_W(t) > \mathrm{HEP}_{\mathrm{CT}} \ \textbf{AND} \ T_{a,\mathrm{amb},W}(t) < 20°\mathrm{C} \end{cases} \tag{8}$$

4. DATA AND PERFORMANCE METRICS

We run simulations for 2 heating (January and February), and 2 cooling season months (July and August) for the climatic conditions of Pasco-TriCities under highly dynamic hourly electricity price (HEP) to test the performance of our proposed controller with the baseline and literature inspired controllers. We assume perfect knowledge of ambient air temperature ($T_{a,\mathrm{amb}}$) and HEP for this study. It is to be noted that day-ahead HEP forecast is required for setting the LP for each day at the start of the day. However, for calculating the trend of HEP (F), and weighted forecasts of ambient temperature ($T_{a,\mathrm{amb},W}$) and HEP (HEP_W), a 5 h ahead forecast window is used.

The metrics used to compare the proposed controller with the baseline and literature inspired controller are HVAC energy usage (E_{HVAC}), HVAC cost (C_{HVAC}) which is the dot product of E_{HVAC} and HEP, nominal thermal discomfort (Ψ_{nom}), and HP cycles (Heating/Cooling Coil signal change from OFF to ON to OFF). The nominal thermal discomfort defines the cumulative deviation of the indoor air temperature from the upper and lower indoor air comfort limits. The nominal thermal discomfort is formulated, with Δt being the granularity of the control actions (considered 5 min) as

$$\Psi_{\text{nom}} = \sum_{t=1}^{T_{\text{end}}} [\max(0, T_{\text{comfort,lower}} - T_{a,\text{ind}}(t)) + \max(0, T_{a,\text{ind}}(t) - T_{\text{comfort,upper}})]\Delta t. \tag{9}$$

$\text{HP}_{\text{signal}} = 1$, when the Heating/Cooling Coil = ON, and $\text{HP}_{\text{signal}} = 0$, when the Heating/Cooling Coil = OFF. The net HVAC coefficient of performance is formulated as $\text{COP}(t) = \frac{T(t)}{P(t)}$ where T is the thermal heating/cooling rate due to the HP, and P is the electrical power usage.

5. RESULTS AND DISCUSSIONS

5.1 Heating season

5.1.1 Timeseries analysis on a representative day: The timeseries analyses of the four controllers for a representative day in the heating season (January 2, represented as 24 − 48 h of the year) is shown in Fig. 4. Figures 4b and 4c show that both the baseline controllers (A) and (B) tries to maintain the indoor air temperature above their respective heating setpoints (with consideration for deadband), regardless of the HEP. As the ambient temperature during the start of the day is low (see Fig. 4a) until about 36 h (i.e., 35:59 h), both the baseline controllers undergo cycling as HP has to frequently turn on. The baseline controllers avoid heating during the high HEP hours between 40 − 43 h (i.e., 40:00 h to 42:59 h), as the ambient temperature also had a rise just before the high HEP hours, allowing sufficient thermal storage in the building envelope to ride off the peak HEP without heating. However, one can easily imagine a (HEP−ambient temperature) combination where the baseline controllers continuously have to keep operating during high HEP periods.

For both the literature inspired and the proposed controller, the LP is important for determining when the preheating occurs. The hours when the HEP is below the LP are 24 − 29 h, 36 − 39 h, and 44 − 48 h. The literature inspired controller seeing the rising trend of the HEP until 29 h (see Fig. 4a), has a higher heating setpoint than the proposed controller leading to more HVAC energy usage (compare Figs. 4h and 4i until 29 h). The heating setpoint choices for the literature inspired controller (see Fig. 4d) in this study are 24 °C, 23 °C and 22 °C when the HEP rises, levels out and decreases respectively. Although the preheat temperature choices for the proposed controller are same as that of the literature, the proposed controller (see Fig. 4e) is able to modulate its preheat temperature setpoint depending on the weighted forecast of the HEP, leading to the decrease of T_{preheat} of the proposed controller from 24 °C to 23 °C at 27 h, whereas for the literature inspired controller $T_{\text{heat,set}}$ remains 24 °C until 29 h. The reduction of T_{preheat} of the proposed controller from 24 °C to 23 °C at 27 h prevents excess preheating, which can undermine the benefits of preheating. After 29 h, the HEP becomes higher than the LP, and both the literature and the proposed controller tries to minimize use of the HP. Note that the T_{preheat} for the proposed controller is only active when in the FLEX mode and HEP ≤ LP (indicated by absence of T_{preheat} in Fig. 4e between 29 − 36 h).

Between 36 − 39 h, HEP < LP, and the trend of the HEP rises, with the literature inspired controller setting $T_{\text{heat,set}}$ to 24 °C, leading to overheating (which is redundant) as the ambient temperature increases until about 38 h. The proposed controller leverages the knowledge of the ambient temperature forecast through T_W and HEP forecast through HEP_W, to set T_{preheat} to 22 and 23 °C, preventing the need for heating. The excess energy usage of the literature inspired controller as compared to the proposed controller between 36 − 39 h can be seen on comparing Figs. 4h and 4i from 36 − 39 h. Between 39 − 44 h, as HEP > LP, both the literature inspired and the proposed controller avoid using the HP, leveraging the thermal storage to keep the indoor air temperature in the thermal comfort zone.

After 44 h, the HEP < LP, with the trend of the HEP falling until 47 h in the literature inspired controller. After 47 h, the trend of the HEP rises in the literature inspired controller due to increases in HEP based on the early hour forecasts (after 52 h) of January 3 (not shown in figures). This increasing trend of HEP is manifested in $T_{\text{heat,set}}$ rising to 24 °C after 47 h (see Fig. 4d). The rise of T_{preheat} to 24 °C after 47 h is unnecessary as the immediate decreases in HEP (until 49 h) is ignored by the literature inspired controller (as it only looks at the two extreme HEP entries in two adjacent horizons), and the HEP in the early hours of January 3 is still quite low (not shown in figures), obviating the need for preheating from so early. In the proposed controller, the thermal energy stored (by preheating) before 44 h was less than in literature, resulting in the $T_{a,\text{ind}}$ dropping below 21.5 °C sooner, necessitating some cycling of HP after 44 h. Note that, although after 44 h, the controller goes in the FLEX mode with HEP ≤ LP from time to time (indicated by intermittent T_{preheat} after 44 h in Fig. 4e), preheating is never activated as $F_2 < F_1$ AND $F_3 < F_1$, indicating the overriding decreasing trend of HEP (especially between 47 − 49 h) − a fine trend in HEP which the literature inspired controller missed out on. Figures 4f, 4g, 4h, and 4i, show that the cumulative cost and electric energy is the least for the proposed controller, without significant thermal discomfort, as $T_{a,\text{ind}}$ still remained within the thermal comfort band of 21.5−24.5 °C.

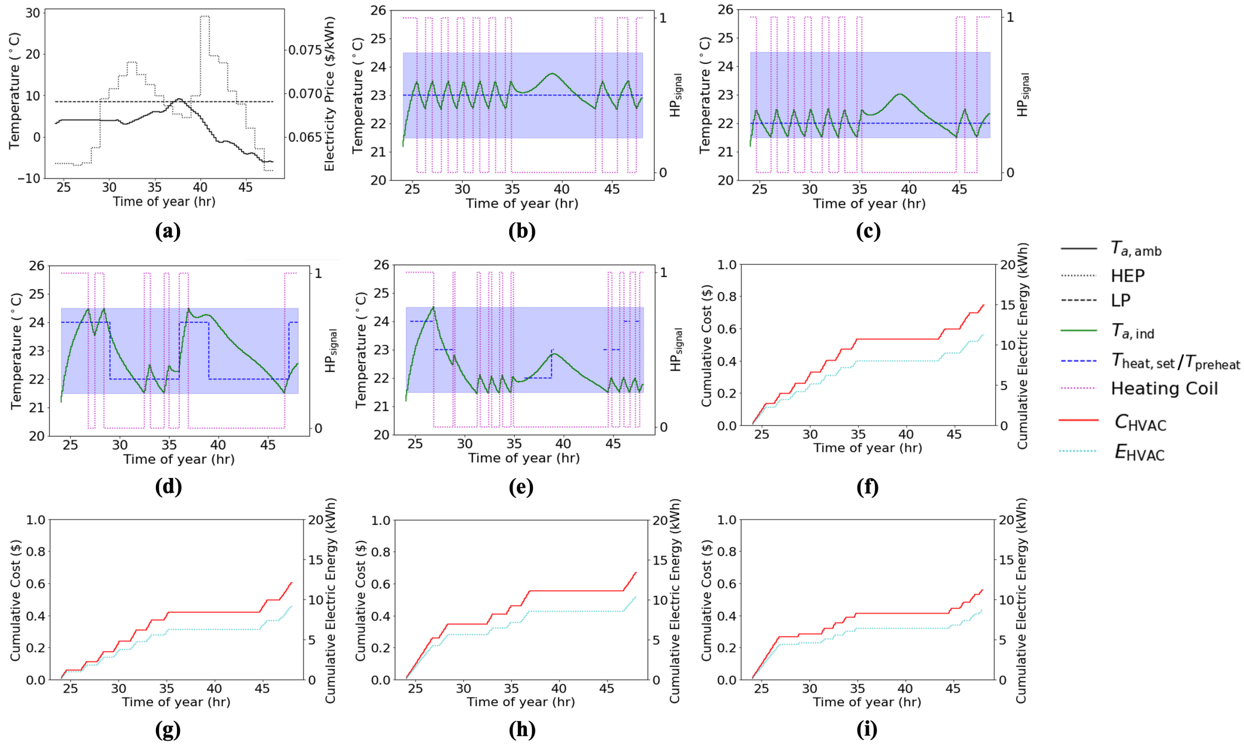


Figure 4: Performance comparison between the four controllers for a representative day in the heating season: (a) Ambient air temperature and hourly electricity price, (b,f) Baseline controller (A), (c,g) Baseline controller (B), (d,h) Literature inspired controller, and (e,i) Proposed controller. The blue filled patch denotes the thermal comfort zone.

5.1.2 Monthly analysis: Table 1 shows that for January the proposed controller outperforms the Baseline controller (A) by 12%, and the literature inspired controller by 5%, while having almost similar performance to the Baseline controller (B) with respect to the HVAC cost. The Baseline controller (B) despite having no predictive capability performs as well as the proposed controller with respect to the HVAC cost because of the increase of ambient temperature before highest HEP periods (see Fig. 4a and Section 5.1.1), thereby storing enough thermal energy in the building envelope to ride off the peak HEP without heating. However, such a (HEP− ambient temperature) combination is not general, and the Baseline controller (B) can lead to heating during high HEP periods in a situation where ambient temperature falls just before the high HEP period, because of the lack of predictive capability, which may lead to higher HVAC costs. The proposed controller has lower nominal thermal discomfort than the Baseline (A) and literature inspired controllers. Although, the nominal thermal discomfort of the proposed controller is quantitatively four times that of the Baseline controller (B), the differences are marginal and mathematical, as relaxed thermal discomfort, calculated using an additional slack of ± 0.5 °C in (9) is 0 Kh for both the Baseline (B) and proposed controller, which however are greater than 0 for the Baseline (A) and literature inspired controller. The total thermal heating energy demand (Heating in Table 1) of the proposed controller is lower than Baseline (A) and literature inspired controller while being slightly more than Baseline (B). The total thermal heating energy demand of the Baseline controller (B) is lowest because of the fixed low heating setpoint of 22 °C throughout, while for the literature inspired and proposed controllers, higher heating/preheating setpoints of 23 and 24 °C are additionally implemented to take advantage of preheating during low HEP periods. The number of HP cycles are least for the literature inspired controller, while being the most for the proposed controller - indicating the quicker response of the proposed controller to finer trends in HEP and ambient temperature unlike the other controllers. The average monthly COP ($\overline{\text{COP}}$) is almost identical for all the controllers, resulting in HVAC energy trend being in general similar to the thermal heating energy demand trend.

The results and trends for February are almost identical to January, with respect to HVAC energy/Heating and HP cycles/COP. HVAC cost is slightly lower in the Baseline controller (B) as compared to the proposed controller. The biggest difference is thermal discomfort − which is significantly more for all the controllers in February as compared to January because of the higher ambient temperatures in February, leading to the indoor air temperature sometimes going above the 24.5 °C upper comfort limit − however cooling is avoided to prevent intra-season HP mode switching. Besides the (lucky) HVAC cost reduction for the Baseline controller (B) under the specific HEP− ambient temperature combination in this work, the monthly analyses in the heating months in general shows the proposed controller achieving a tradeoff between lower HVAC cost and higher HP cycles, as compared to the Baseline (A) and literature inspired controllers.

Table 1: Monthly performance metrics of the four controllers in the heating season months of January and February

	January						February					
Controller	E_{HVAC}	C_{HVAC}	Ψ_{nom}	**Heating**	HP_{cycle}	$\overline{COP}$	E_{HVAC}	C_{HVAC}	Ψ_{nom}	**Heating**	HP_{cycle}	$\overline{COP}$
Baseline (A)	426 kWh	$28.7	5.8 Kh	751 kWh	234	1.76	217 kWh	$13.8	150.1 Kh	366 kWh	106	1.69
Baseline (B)	375 kWh	$25.2	0.2 Kh	672 kWh	230	1.79	177 kWh	$11.3	78.4 Kh	301 kWh	98	1.71
Literature	377 kWh	$26.4	9.0 Kh	731 kWh	164	1.79	215 kWh	$13.2	169.6 Kh	372 kWh	92	1.73
Proposed	383 kWh	$25.1	0.8 Kh	687 kWh	266	1.79	188 kWh	$11.6	98.2 Kh	324 kWh	126	1.72

5.2 Cooling season

5.2.1 Monthly analysis: Table 2 shows that in the cooling season, the proposed controller outperforms the other controllers with respect to the HVAC cost. Note that contrary to the heating season, in the cooling season, the relaxed Baseline controller (B) without predictive precooling capability is left with excess thermal energy in the building envelope during high HEP periods, necessitating more cooling demand during high HEP periods as compared to the literature inspired and proposed controller, driving up HVAC costs. The nominal thermal discomfort is most in the proposed controller, however the differences are marginal as the relaxed thermal discomfort is 0 Kh for all the controllers. The higher $\overline{COP}$ of the proposed controller along with lower thermal cooling energy demand facilitates lower HVAC energy usage. The literature inspired controller cycles most frequently due to excessive overcooling, leading to indoor air temperature dropping below 21.5 °C frequently − rather than cycling more due to quicker response to finer trends in ambient temperature and HEP like the proposed controller. The cooling month analyses show the proposed controller of being able to achieve a better tradeoff between lower HVAC cost and higher HP cycles, than the other controllers.

Table 2: Monthly performance metrics of the four controllers in the cooling season months of July and August

	July						August					
Controller	E_{HVAC}	C_{HVAC}	Ψ_{nom}	**Cooling**	HP_{cycle}	$\overline{COP}$	E_{HVAC}	C_{HVAC}	Ψ_{nom}	**Cooling**	HP_{cycle}	$\overline{COP}$
Baseline (A)	787 kWh	$57.0	0 Kh	2221 kWh	745	2.86	666 kWh	$45.2	0 Kh	1945 kWh	750	2.97
Baseline (B)	742 kWh	$53.8	0 Kh	2122 kWh	654	2.89	628 kWh	$42.7	0 Kh	1855 kWh	596	2.98
Literature	756 kWh	$53.1	0.1 Kh	2203 kWh	906	2.98	641 kWh	$42.2	0.1 Kh	1927 kWh	824	3.06
Proposed	699 kWh	$49.0	6.2 Kh	2134 kWh	869	3.07	601 kWh	$39.8	4.3 Kh	1864 kWh	789	3.11

6. CONCLUSIONS AND FUTURE WORK

We developed a scalable, computationally inexpensive, yet novel advanced predictive rule based controller (PRBC) for HP applications in residential buildings under highly dynamically varying hourly electricity pricing (HEP) to reduce electricity costs. The advanced PRBC uses the current indoor air temperature inside the conditioned space, and day ahead predictions of HEP and ambient temperature to determine the preheating or precooling actions to reduce HVAC costs/energy without noticeable increase of indoor thermal discomfort. The results of the proposed advanced PRBC are compared with two fixed indoor temperature setpoint baseline controllers (one industry standard, another more relaxed, and both without any predictive capability) and a PRBC based literature inspired controller for two heating season and two cooling season months for the climatic conditions of Pasco-TriCities, Washington.

The advanced PRBC is shown to identify and respond quickly to finer trends in HEP and ambient temperature than the other controllers resulting, in general, of HVAC cost and energy reduction, at the expense of more heat pump (HP) ON/OFF cycles. The thermal discomfort of the advanced PRBC is comparable to the other controllers, proving the efficacy of the proposed PRBC in judiciously preheating/precooling during low HEP periods to avoid heating/cooling during high HEP periods. The advanced PRBC performs significantly better in the cooling season than the heating season, achieving as high as 14%, 9%, and 8% in monthly cost savings, and 11%, 6%, and 8% in monthly HVAC energy savings, as compared to the industry standard, relaxed baseline and literature inspired controllers respectively.

One of the novel features of the present work is to calculate the future trend of the HEP and ambient temperature in a realistic way by giving proportional weightage to the forecasted values, prioritizing closer time steps to the present, due to the intuitive principle that forecasting accuracy diminishes with greater temporal distance from the present. However, for the present work, perfect forecasts of HEP and ambient temperature are used. The real benefit of the proportional weightage to forecasted values and its comparison to other controllers (which weights all forecast values equally) will be manifested under imperfect forecasts (which is closer to reality), and will be explored in future works.

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