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Integrating Smart Thermostat and Weather Forecasting Data for Real-Time HVAC Efficiency Optimization in Residential Buildings

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Abstract

Heating, ventilating, and air conditioning (HVAC) systems account for significant portion of residential buildings' energy consumption, especially in cold climate regions. Previous studies have shown the growing importance of smart thermostats. However, many existing studies are based on reviews, simulations, or large datasets rather than simple real-world studies. This paper studies a forecast informed thermostat control strategy for improving heating efficiency in a single-family residential building in Minnesota with 2,256 ft^2 area where the building is equipped with a forced air natural gas furnace and a smart Sensi thermostat. With two weeks of study, week 1 was the data collection under a conventional fixed setpoint condition. This served as baseline data. For week 2, thermostat settings were manually adjusted using short-term weather forecasts. The baseline week produced the model y = 8.946 – 0.1017x, while week 2 produced y = 7.149-0.06102x signifying the furnace runtime improved by 22.34% at 0^0F compared to baseline week. This finding suggests that integrating smart thermostat data with short-term weather forecasts can provide a practical and low-cost approach for improving HVAC efficiency in residential buildings.

Keywords
HVAC; smart thermostat; weather forecasting; HVAC efficiency.

1. Introduction
Heating, ventilation, and air conditioning (HVAC) systems are among the largest energy end uses in buildings. Prior studies report that HVAC systems account for nearly 40-60% of total energy consumption in the buildings in the United States. Also, 20% of the total energy consumption in the US comes from HVAC systems. (Pérez-Lombard , Ortiz , & Pout, 2008). Around 42% of the residential energy consumption in the United States comes from space heating alone. Natural gas is the primary source of heating fuel in the colder regions (Residential Energy Consumption Survey (RECS), 2025). Traditional thermostats rely on static temperature setpoints or fixed schedules, which fail to consider dynamic external factors like outdoor temperature, solar gain, wind speed, or occupant behavior. (Brandi, Fiorentini, & Capozzoli , 2022). There are modern smart thermostats which help to schedule the heating and provide

remote access. However, most deployments remain reactive. The trigger to activate thermostat is caused after indoor temperature drifts or after human input. Heating demand is strongly driven by external factors. The external factors that cause heating demand to change which could be predicted easily are outdoor temperature, solar gains, wind, and occupancy (Zhuang , et al., 2013).

Although prior studies confirm the benefits of predictive HVAC control, there are several gaps that need to be addressed. There has been a limited validation in the experimental field which covers the single-family residential building. Also, the prior focus has not been on natural gas heating and the cost optimization. Also, the experimental results with real time thermostat runtime and indoor temperature data with respect to outdoor temperature is limited. This paper proposes a forecast aware control strategy that uses available weather predictions to schedule furnace time to reduce furnace run time decreasing the energy usage. Data from smart thermostat, portable temperature sensos in the multiple areas of the house, and online weather forecasts are used for this paper.

1.1 Objectives

The objective of this study is to develop and evaluate a short-term weather forecast informed thermostat control strategy for improving heating efficiency in a single-family residential building. The study first analyzes relationships between outdoor temperature and furnace runtime under traditional thermostat control settings. Then the study implements forecast-informed thermostat settings using short-term weather predictions. Finally, the study compares furnace runtime between baseline controls settings and forecast-informed thermostat control settings and estimates the reduction in furnace runtime with the help of proposed strategy.

1.2 Research Questions

This study focuses on finding the answer to the following research questions.

1. How does outdoor weather affect heating energy demand in residential spaces?
2. Can short-term weather forecasts be used to predict indoor thermal load and pre-adjust heating cycles efficiently?
3. Does forecast-informed thermostat control reduce furnace runtime compared to conventional thermostat control?

2. Methods

2.1 Experimental design

A two-week experimental case study was conducted in a single-family house to compare baseline fixed-setpoint thermostat control with forecast-informed thermostat control. Outdoor temperature was used as the primary explanatory variable, and daily furnace runtime was used as the response variable.

2.2 Case Study Building

This case study uses data from a four-bedroom single-family house. The specification of the house where data was collected is:

Total area: 2,256 ft^2
Basement: Two bedrooms
First floor: Two bedrooms
Heating system: Forced-air natural gas
Thermostat: Sensi smart thermostat

2.3 Data Acquisition and Control Procedure

There are two primary sources of data collected:
Indoor data included:

- Smart thermostat historical records.
- Spot temperature measurements using a laser temperature gun.

Since indoor temperature is not uniform throughout the house, the laser temperature gun was used only as a supplemental indoor temperature check rather than the primary response variable. The primary response variable was furnace runtime which was obtained by the dashboard of smart thermostat. For spot temperature measurements using laser temperature gun, area around air vents, windows, area with direct sunlight, exterior walls, and heat producing appliances was avoided. Temperatures from each rooms, living room, bathroom, and utility rooms were recorded and average temperature was calculated. Same spots were measured for the entire study (Figure 1).

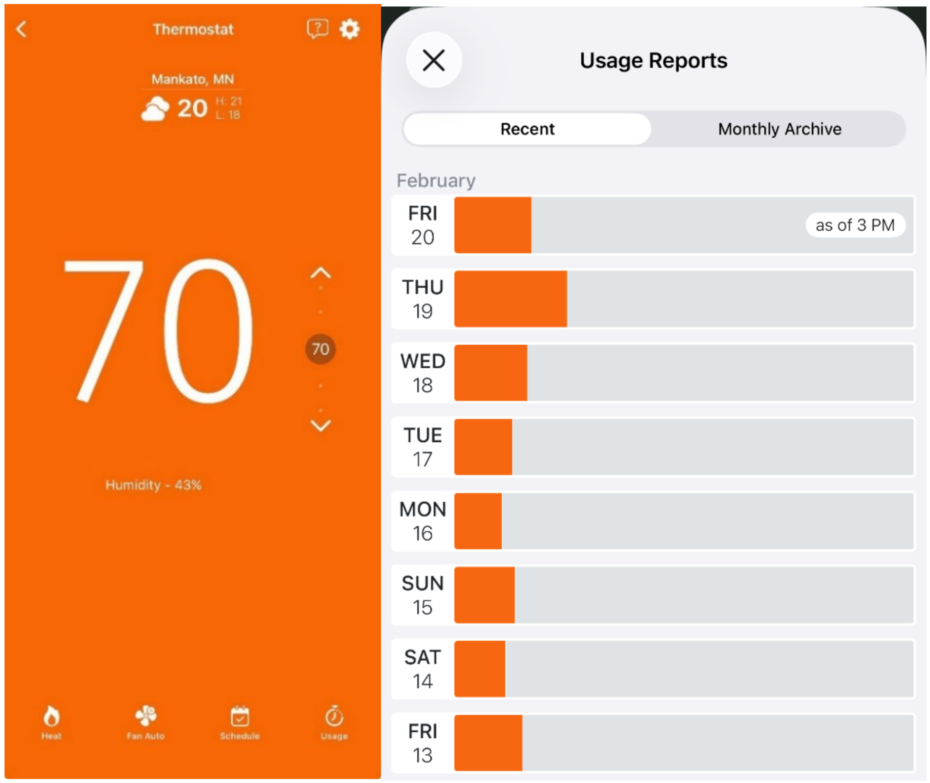

Figure 1. Sensi Smart Thermostat Dashboard

Outdoor data

- Real-time and forecast data collected from online weather service called Weather Underground.

The data was collected in two different weeks. Below are the details of the data collection procedures and plans.

2.3.1 Week 1: Baseline fixed-setpoint control

For the baseline fixed-setpoint control week, the thermostat was held at a fixed setpoint and allowed to cycle automatically. No weather forecast adjustment was applied. Recorded variables included furnace runtime, indoor temperature profile, outdoor temperature, and thermostat status.

2.3.2 Week 2: Weather Forecast Integrated Data Collection

During Week 2, the thermostat was manually adjusted within a limited comfort band of 69°F to 71°F based on short-term weather forecasts. The adjustment rule was not applied as a cumulative proportional rule. Instead, when the two-hour forecast indicated an outdoor-temperature increase of at least 3°F, the thermostat setpoint was reduced by up to 1°F. When the forecast indicated an outdoor-temperature decrease of at least 3°F, the thermostat setpoint was increased by up to 1°F or maintained at the higher comfort setpoint to reduce later heating demand. Larger outdoor-temperature changes, such as 6°F, did not automatically produce a 2°F thermostat adjustment because the control strategy was capped to avoid indoor comfort disturbance.

2.4 Forecasting and Validation Model

Week 1 data was utilized as the training dataset to assess the regression model's forecasting ability. Thermostat run time was used as the dependent variable and outdoor temperature as the independent variable in a linear regression model. The estimated thermostat run time was then calculated by applying the resulting regression equation to the outdoor temperature data from Week 2. Mean absolute error and mean squared error were used to compare the predicted values with the actual run time for Week 2.

$$Predictive\ Furnance\ Run\ Time = intercept + \ slope * daily\ Average\ Temperature$$

2.4 Squared Error and Absolute Error

Mean absolute error (MSE) represents the average absolute errors in hours per day. Mean standard error represents the average squared prediction error and gives more weight to larger errors. These metrics were used to evaluate whether the regression model only fits the collected data or can also provide reasonable prediction of furnace runtime for the second week.

3. Data Collection

3.1 Baseline week data

The outdoor temperature was collected via weather underground website. For indoor weather data, Sensi smart thermostat's dashboard was used. Thermostat temperature, run per day, and thermostats status was measured. It was recorded if the furnace is on or off during the given time. For thermostat status, 1 is used when the furnace is on and 0 is used when the furnace is off. The collected data is shown on table 1.

Table 1. Week 1 data

DateTime	Outdoor Temperature	Thermostat Temp	Run time per day (hours)	Thermostat Status
11/17/2025 6:00	38	70	5	1
11/17/2025 8:30	38	70	5	1
11/17/2025 18:00	41	70	5	0
11/17/2025 20:00	40	70	5	1
11/17/2025 23:59	38	70	5.5	0
11/18/2025 6:00	35	70	5.5	0
11/18/2025 8:30	34	70	5.5	0
11/18/2025 18:00	39	70	5.5	1
11/18/2025 20:00	38	70	5.5	0
11/18/2025 23:59	38	70	5	0
11/19/2025 6:00	38	70	5	1
11/19/2025 8:30	38	70	5	1
11/19/2025 18:00	42	70	5	1
11/19/2025 20:00	42	70	5	0
11/19/2025 23:59	43	70	5	1
11/20/2025 6:00	42	70	4.5	1

11/20/2025 8:30	42	70	4.5	0
11/20/2025 18:00	41	70	4.5	0
11/20/2025 20:00	37	70	4.5	0
11/20/2025 23:59	31	70	4.5	1
11/21/2025 6:00	26	70	5.5	1
11/21/2025 8:30	33	70	5.5	0
11/21/2025 18:00	41	70	5.5	1
11/21/2025 20:00	36	70	5.5	0
11/21/2025 23:59	34	70	5.5	0

(Mankato, MN Weather History, n.d.)

The outdoor temperature for week 1 could be visualized from figure 2.

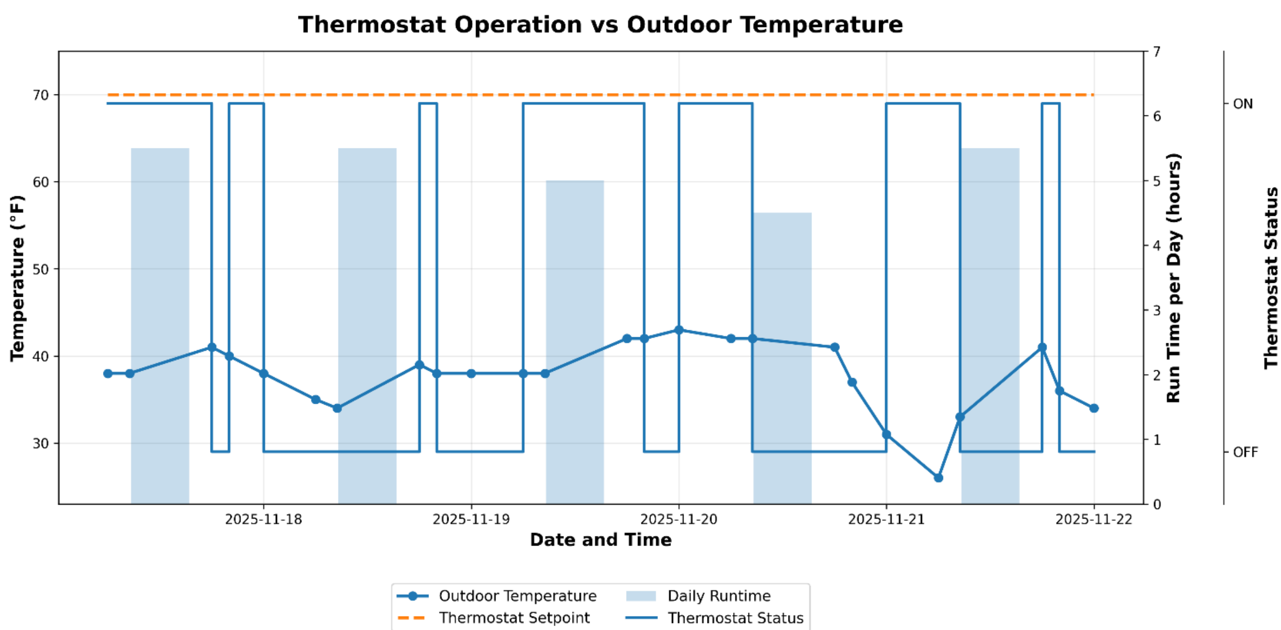

Figure 2. Trends for baseline week

3.2 Forecast-informed week data

For the forecast informed week data collection, the thermostat setpoint was adjusted using the two-hour weather forecast rule described above. The same variables were recorded to support comparison with the baseline week. The collected forecast-informed data collected is summarized in Table 2.

Table 1. Week 2 data

Date	Time	DateTime	Temperature	Thermostat Temp	Run time per day	Thermostat Status
24-Nov	6:00 AM	11/24/2025 6:00	40 °F	70	4.8	0
24-Nov	9:00 AM	11/24/2025 9:00	40 °F	70	4.8	0
24-Nov	6:00 PM	11/24/2025 18:00	46 °F	69	4.8	0
24-Nov	9:00 PM	11/24/2025 21:00	44 °F	69	4.8	0
24-Nov	11:59 PM	11/24/2025 23:59	43 °F	70	4.8	0
25-Nov	6:00 AM	11/25/2025 6:00	42 °F	70	4.6	0
25-Nov	9:00 AM	11/25/2025 9:00	42 °F	69	4.6	0
25-Nov	6:00 PM	11/25/2025 18:00	38 °F	70	4.6	1
25-Nov	9:00 PM	11/25/2025 21:00	34 °F	70	4.6	1
25-Nov	11:59 PM	11/25/2025 23:59	31 °F	71	4.6	1
26-Nov	6:00 AM	11/26/2025 6:00	27 °F	71	5.4	1
26-Nov	9:00 AM	11/26/2025 9:00	24 °F	70	5.4	0
26-Nov	6:00 PM	11/26/2025 18:00	25 °F	71	5.4	1
26-Nov	9:00 PM	11/26/2025 21:00	25 °F	70	5.4	0
26-Nov	11:59 PM	11/26/2025 23:59	23 °F	71	5.4	1
27-Nov	6:00 AM	11/27/2025 6:00	22 °F	71	5.8	1
27-Nov	9:00 AM	11/27/2025 9:00	24 °F	70	5.8	0
27-Nov	6:00 PM	11/27/2025 18:00	24 °F	71	5.8	1
27-Nov	9:00 PM	11/27/2025 21:00	19 °F	71	5.8	1
27-Nov	11:59 PM	11/27/2025 23:59	17 °F	71	5.8	1
28-Nov	6:00 AM	11/28/2025 6:00	14 °F	71	6.2	1
28-Nov	9:00 AM	11/28/2025 9:00	16 °F	71	6.2	1
28-Nov	6:00 PM	11/28/2025 18:00	25 °F	70	6.2	0
28-Nov	9:00 PM	11/28/2025 21:00	25 °F	70	6.2	0

28-Nov	11:59 PM	11/28/2025 23:59	23 °F	70	6.2	0

Note: The outdoor temperature values shown in Table 2 are recorded outdoor temperatures at each observation time. The thermostat setpoint was adjusted using short-term forecast information and was limited to a 69°F–71°F comfort range. Therefore, the setpoint adjustment should not be interpreted as a direct proportional change for every 3°F change in the recorded outdoor temperature.

The outdoor temperature for week 2 could be visualized from figure 3.

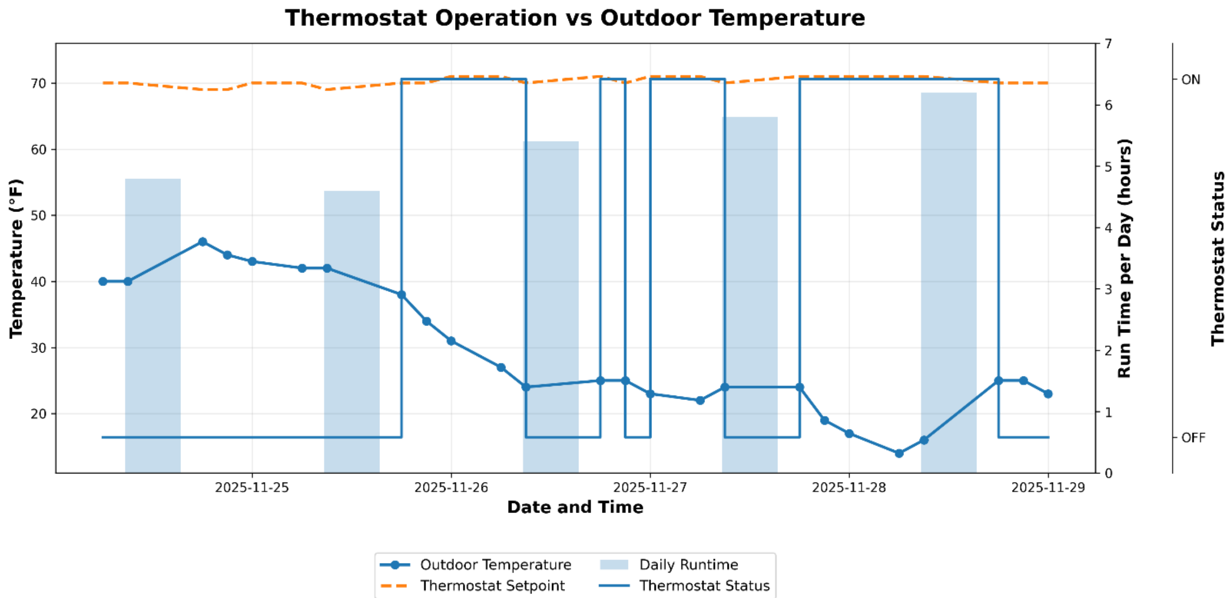

Figure 3. Trend for forecast-informed week

4. Results and Discussion

4.1 Baseline week

During the baseline week, furnace runtime increased as outdoor temperature decreased. The regression output in Figure 4 indicates a statistically significant negative relationship ($p < 0.05$) between average outdoor temperature and average daily furnace runtime.

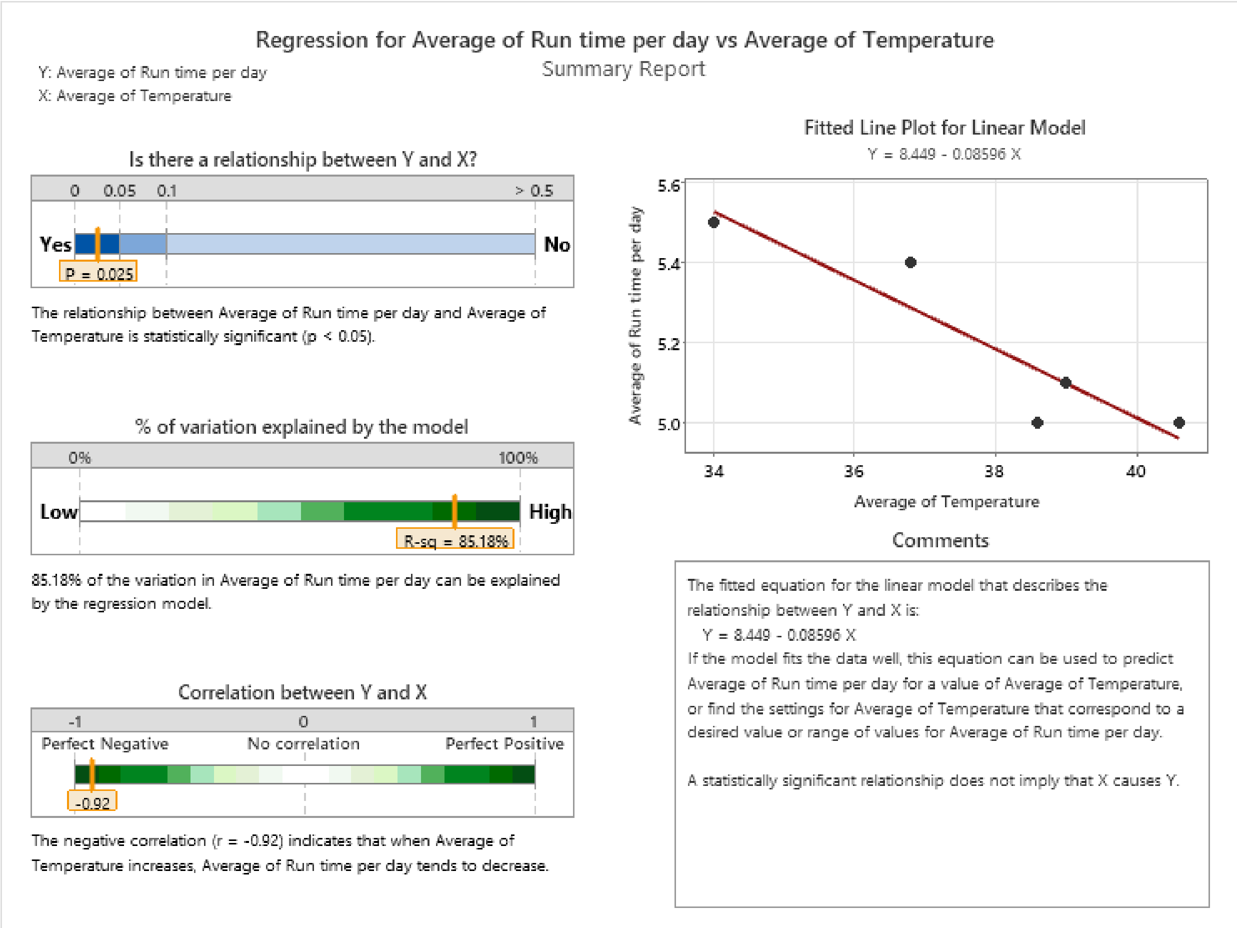

Figure 4: Correlation between furnace run time and outdoor temp - Week 1

The regression equation which explains the relationship between Furnace runtime and average temperature for week 1 is given by equation 1. This relation could be seen in figure 4. The slope of week 1 regression line is -0.1017. This indicates that for every 1F increase in outdoor temperature, the furnace runtime decreases by approximately 0.10 hours (6 minutes) a day.

$$Furnance\ Run\ Time = 8.946 - 0.1017 * Average\ Temperature \qquad Equation\ 1$$

4.2 Forecast-Informed Data

The relationship between furnace runtime per day and average temperature is shown in the regression analysis in figure 5. We could observe a similar downward trend in the relationship between these two.

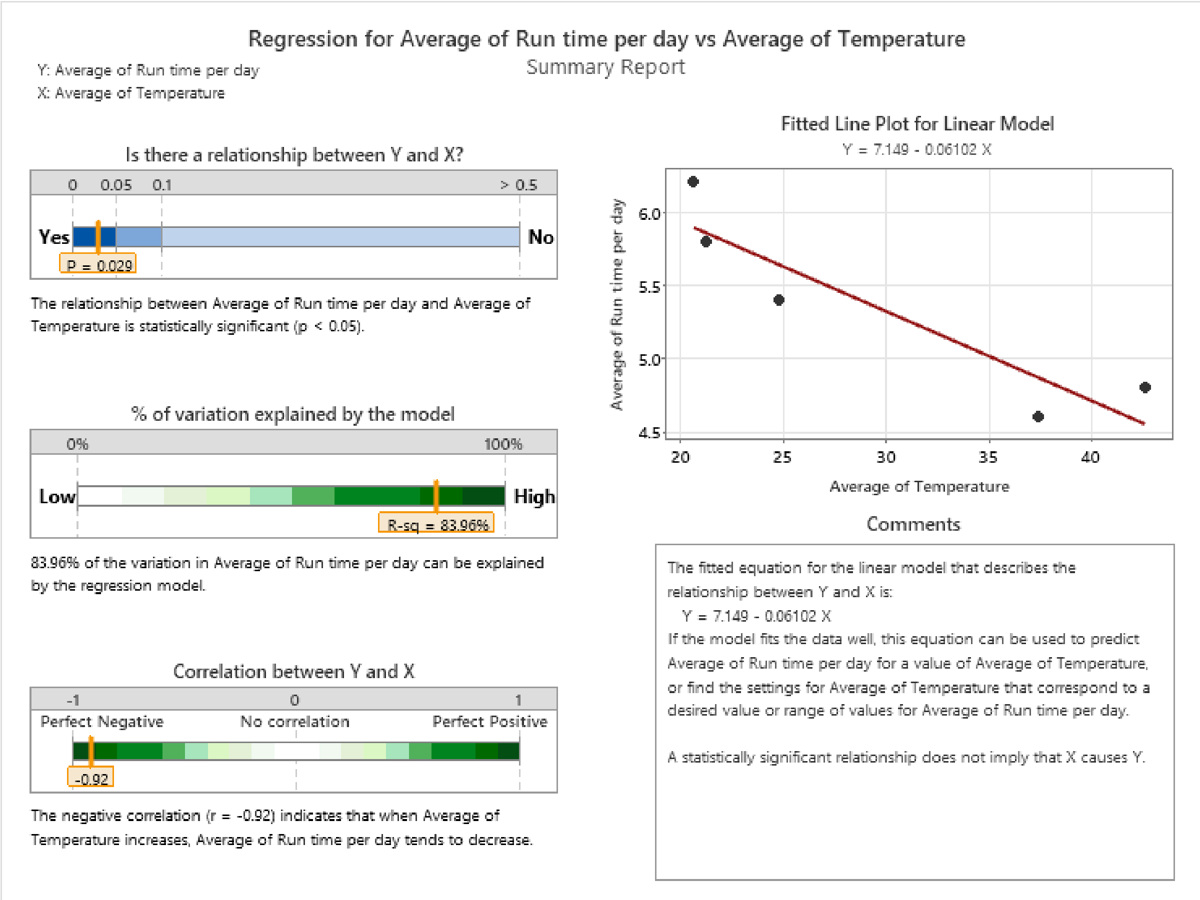

Figure 5: Correlation between furnace run time and outdoor temp- Week 2

The regression equation which explains the relationship between Furnace runtime and average temperature for week 2 is given by equation 2. This relation could be seen in figure 5.

$$Furnance\ Run\ Time = 7.149 - 0.06102 * Average\ Temperature \qquad \text{Equation 2}$$

4.3 Forecast Validation

The Week 1 regression model produced a mean absolute error of 0.68 hr/day and a mean squared error of 0.56 $(hr/day)^2$ when applied to Week 2 data. This indicates that, on average, the predicted furnace runtime differed from the observed runtime by approximately 0.68 hours per day (Figure 6).

Table 2 Absolute Error and Square Error

Date	Avg Outdoor Temp (°F)	Actual Runtime (hr)	Predicted Runtime (hr)	Absolute Error	Squared Error
11/24/25	42.60	4.80	4.78	0.02	0.00
11/25/25	37.40	4.60	5.23	0.63	0.40
11/26/25	24.80	5.40	6.33	0.93	0.86
11/27/25	21.20	5.80	6.64	0.84	0.71
11/28/25	20.60	6.20	6.69	0.49	0.24

From table 3,
MAE= 0.68 hr/day

MSE = 0.56 $(hr/day)^2$

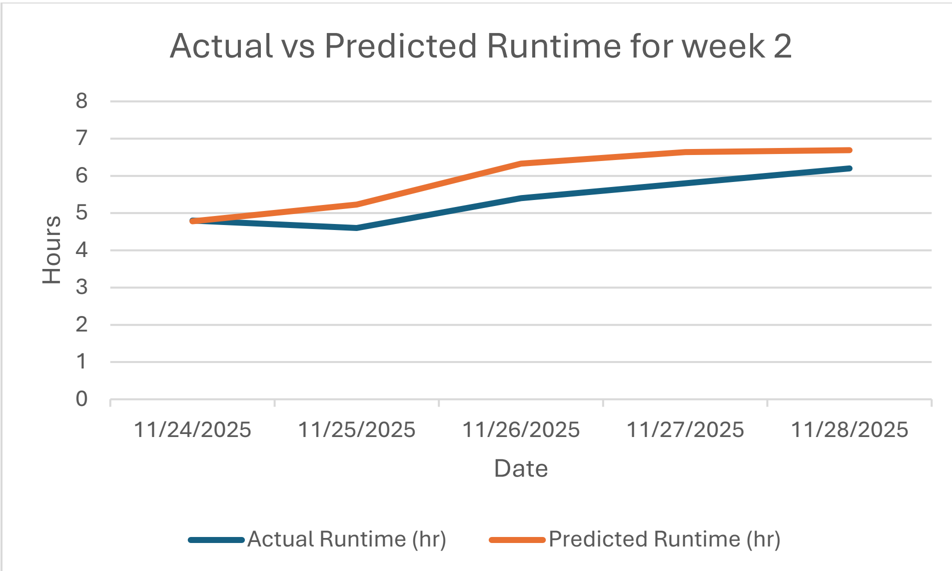

Figure 6: Actual vs Predicted Runtime for week 2

4.4 Comparative Interpretation

Comparing Equations (1) and (2), the baseline slope (-0.1017) indicates an approximate 0.10-hour/day decrease in furnace runtime for each 1°F increase in outdoor temperature. The forecast-informed slope (-0.06102) corresponds to an approximate 0.06-hour/day decrease for the same temperature increase.

The intercept changed from 8.946 hours/day in the baseline week to 7.149 hours/day in the forecast-informed week. This lower intercept suggests reduced predicted furnace runtime under colder outdoor conditions, which is the primary efficiency indicator in this short field study.

In addition to comparing regression slopes and intercepts, the week 1 baseline regression model was utilized for predicting week 2 furnace runtime. The calculation showed 0.68 hr/day of MAE and 0.56 $(hr/day)^2$ of MSE. MAE indicates that the predicted furnace runtime differed from the observed runtime by 0.68 hours (41 minutes) per day on average. This level of error is reasonable for the short study with limited data. The MSE was calculated 0.56 $(hr/day)^2$, which brought the RSME to 0.75 hr/day (45 mins/day). This shows that the regression model used provides a reasonable but preliminary level of forecasting accuracy. At an outdoor temperature of 0°F, the study reported a projected furnace-runtime reduction of 22.34% compared with the baseline condition.

5. Conclusion

This study showed the impact of integrating short-term weather forecasts into residential thermostats to control indoor temperature. Regression analysis from this study shows that the forecast aware control week (week-2) has the optimized use of gas than baseline week (week 1). The Y-intercept for week 1 was 8.946 while it reduced to 7.149 in week 2. This signifies that having short term weather predictions integrated into thermostat helps reduce the time of furnace runtime by 22.34% as compared to traditional temperature control when the temperature is 0F. Although the slope of week 1 regression line was -0.1017 indicating that for every 1F increase in outdoor temperature, the furnace runtime decreased by approximately 0.10 hours (6 minutes) a day compared to the slope of week 2 regression line which was -0.06102, indicating that for every 1F increase in outdoor temperature, the furnace runtime decreases by approximately 0.06 hours (3.6 minutes) a day. The more important result is that the week 2 regression line has lower intercept, indicating lover predicted furnace runtime under colder conditions. The mean absolute error and mean squared errors were calculated to be 0.68 hr/day and 0.56 $(hr/day)^2$ respectively. This showed that the model provided a reasonable but preliminary level of forecasting accuracy.

Overall, the integration of short-term weather forecast data to thermostat helps to reduce the gas usage and ultimately helps reduce energy cost. As this research only focuses on the outdoor temperature data to adjust the thermostat, future research needs to be done including other weather parameters such as wind-speed and humidity and look for long term savings. Also, for this research, thermostat was controlled manually. For the optimal results, thermostat needs to be programmed to adjust itself by looking at the weather predictions.

References

Pérez-Lombard, L., Ortiz, J., & Pout, C. A review on buildings energy consumption information. ScienceDirect, 394–398, 2008.

Brandi, S., Fiorentini, M., & Capozzoli, A. Comparison of online and offline deep reinforcement learning with model. Elsevier, 2022.

Mankato, MN Weather History. Retrieved from Weather Underground, 2025. https://www.wunderground.com/history/daily/us/mn/mankato/KMKT/date/2025-11-28

Randall, R. B., & Antoni, J. Rolling element bearing diagnostics—A tutorial. Mechanical Systems and Signal Processing, 25(2), 485–520, 2011. https://doi.org/10.1016/j.ymssp.2010.07.017

Residential Energy Consumption Survey (RECS). Retrieved from U.S. Energy Information Administration, 2025. https://www.eia.gov/consumption/residential/

Zhuang, D., Gan, V. J., Tekler, Z. D., Chong, A., Tian, S., & Shi, X. Data-driven predictive control for smart HVAC system in IoT-integrated buildings with time-series forecasting and reinforcement learning. Applied Energy, 2013.

Biographies

Yaman Pandey is a Master of Science student pursuing a degree in Manufacturing Engineering Technology at Minnesota State University, Mankato, USA. He earned a Bachelor of Science degree in Mechanical Engineering from the same University. He has over 3 years of work experience. He works as a Reliability Engineer at dsm-firmenich. He also has Engineer-in-Training (EIT) certification from Minnesota Board of Architecture, Engineering, Land Surveying, Landscape Architecture, Geoscience and Interior Design. He also served as a treasurer of the student chapter of The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) in 2022.

Dr. Pawan Bhandari is an Assistant Professor at Minnesota State University, Mankato. He received a PhD in Technology Management from Indiana State University, USA. He has earned Master and bachelor's in manufacturing engineering technology from Minnesota State University, Mankato. He has over 10 years of work experience. He has worked as Principal health system engineer at Mayo Clinic before working as faculty at MNSU. He is also certified Quality improvement Associate and certified Six Sigma Blackbelt from ASQ. His research interest is in Quality Systems, Six Sigma and Lean Manufacturing