DEVELOPMENT OF A DATA-DRIVEN MODEL FOR THE ENERGY OPTIMIZATION OF A MULTI-ZONE HEATING, VENTILATION, AND AIR-CONDITIONING SYSTEM

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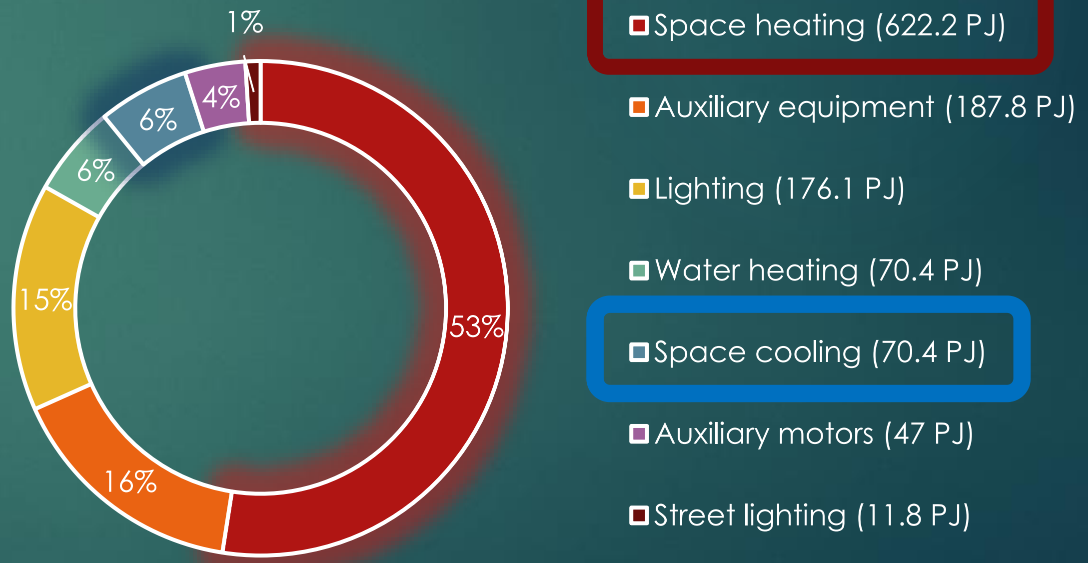
HVAC System Energy Consumption

- About 40% to 60% of buildings' energy consumption is devoted to Heating, Cooling, and Air Conditioning (HVAC)
- **In Canada,** 53% of is consumed by space heating in commercial/institutional buildings.
- About 30% of the consumed energy in HVAC systems is wasted.

Main Reasons:

- Poor management and maintenance of HVAC
- System faults
- Inefficient control strategies



Commercial/institutional energy use by end-use in Canada, 2018

Current HVAC Systems and Data-Driven Systems Application Differences

- **Current HVAC System**
  - Designed by humans
  - Schedule or rule-based programming
  - Not adaptive to unexpected status
  - Prone to faults

- **Data-driven System**
  - Learn and improve over time
  - Enables BMS to respond dynamically to different conditions
  - Autonomous & Adaptive
  - Sustainable

Data-Driven Modeling

- *Data-driven modeling could replace sophisticated physics-based models [6]*
- *High capability in handling real-time events [7]*
- *Strong ability in pattern recognition and extraction in complex and noisy data [8]*
- *The capability of handling external and internal disturbances [11]*
- *Reliable tool for optimizing HVAC system set points when exposed to disturbances [11]*

Research Gap Analysis

- Limited research exists on the application of data-driven modeling for indoor temperature prediction and energy optimization in educational buildings.
- Lack of consideration of single-zone predictions versus multiple-zone ones.
- Lack of explicit explanations of data preprocessing and parameter selection.
- Limited training and test periods for data-driven models.

Main Objectives

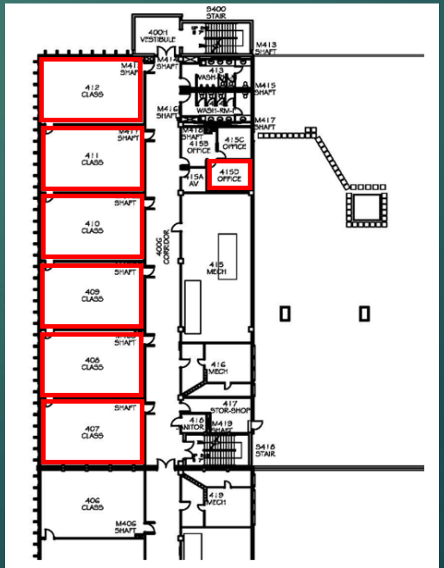
- Objective 1. To propose a highly accurate model to predict indoor temperatures in a multi-zone HVAC system.
- Objective 2. To optimize the energy consumption of the HVAC system.

Detailed Objectives

- **To develop methodologies for data preprocessing and parameter selection.**
- **To explore various data-driven algorithms.**
- **To compare the performance of data-driven models.**
- **To propose a strategy for energy optimization.**

Case Study

- NE01 Building is located at 3700 Willingdon Avenue Burnaby, BC on the main campus of the British Columbia Institute of Technology.
  - The facility is four (4) stories,
  - totals approximately 20,077 SM in the area
  - constructed in approximately 1977
- The data and parameters of AHU07 (one of the AHUs in the NE01) were studied,
- AHU07 serves the loads for seven interior zones on the fourth floor of NE01.
- Studied area consists of six classrooms and one office,
- Each zone has its own Variable Air Volume (VAV) box



Supplied zones info by AHU7

VAV Box Number	Room No.	Description
VAV 4-1	412	Classroom
VAV 4-2	411	Classroom
VAV 4-3	410	Classroom
VAV 4-4	409	Classroom
VAV 4-5	408	Classroom
VAV 4-6	407	Classroom
VAV 4-7	415D	Office

Selected Parameters

Selected set of parameters from the HVAC system.

AHU Parameters

VAVs Parameters

ID	Parameter Name	Description	Unit	No.
01	OAT	Outdoor weather temp.	°C	1
02	AHU7_SAT	AHU7 Supply air temp. after heating coil	°C	1
03	AHU7_SAT_SP	AHU7 supply air temp. set point	°C	1
04	AHU7_EF_SPD	AHU7 Return Fan speed	%	1
05-11	VAV_x^1_SAT_SP	VAV_x^1 supply air temp. set point	°C	7
12-18	VAV_x^1__SAT	VAV_x^1 supply air temp.	°C	7
19-25	VAV_x^1_RT	Room temp. in each zone supplied by VAVs	°C	7
26	horiz_solar_rad	Roof horizontal solar radiation	W/M^2	1

Schedule-based features.

Scheduled Based Parameters

ID	Variables	Parameters Description	No.
27	Day of Week	Weekdays vs Weekend	1
28-30	24 Hours	Daytime, evening, night	3

Selected Algorithms

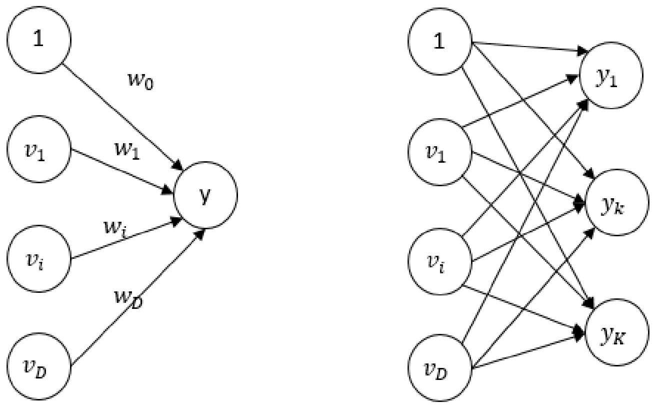
- Five algorithms were selected to model indoor temperature models
  - Extra Trees
  - Random Forest
  - Multilayer Perceptron (MLP)
  - Long Short-Term Memory (LSTM)
  - Convolutional Neural Networks (CNNs)

Tree Based Algorithms

Deep Learning Algorithms

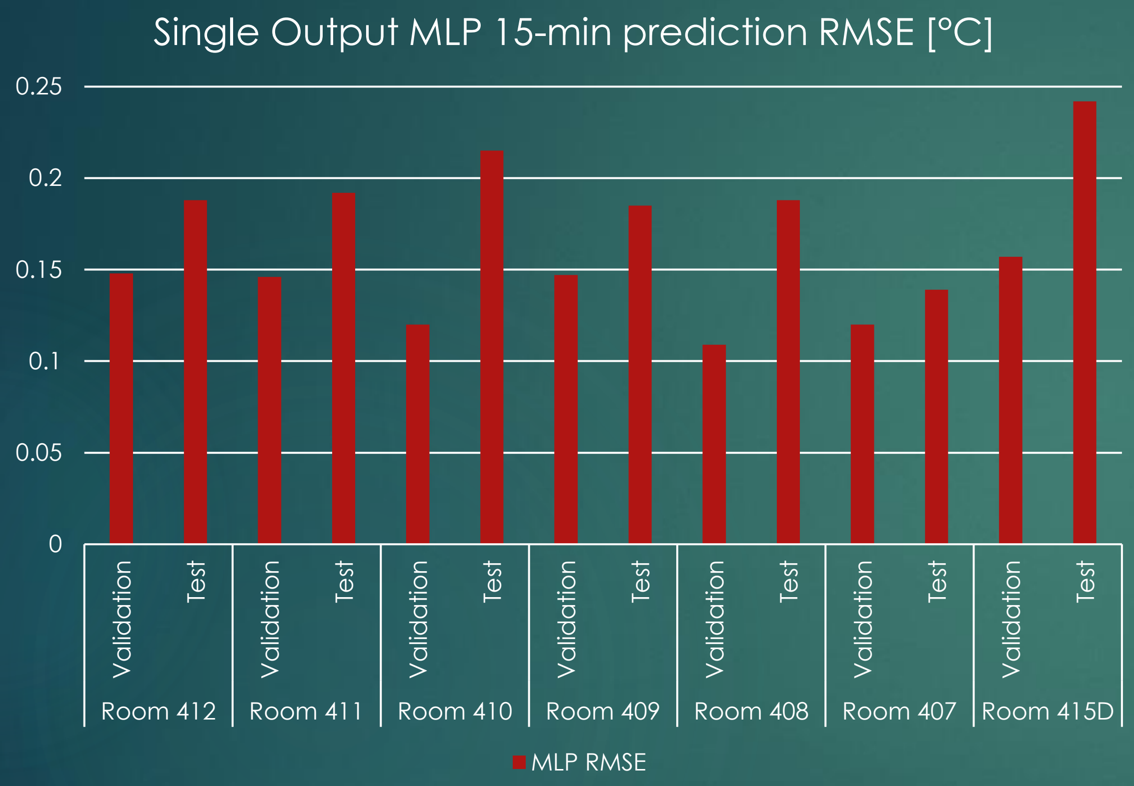
Single Zone vs. Multi-Zone HVAC System

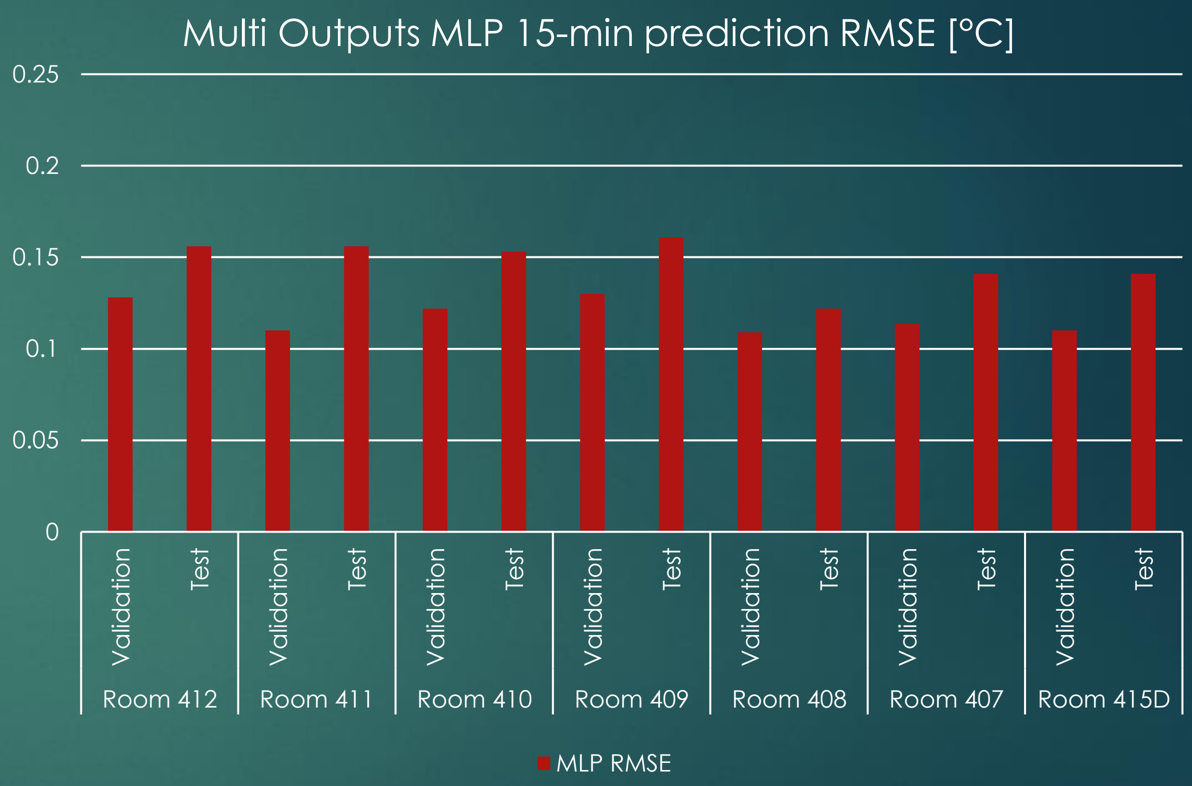
- Single Output Modeling
  - Involves a single target variable
  - Captures the relationships between input features and a specific outcome
- Multi output Modeling
  - Has multiple target variables
  - Captures dependencies and correlations among different variables to predict target variables



Single Output   Multiple Output

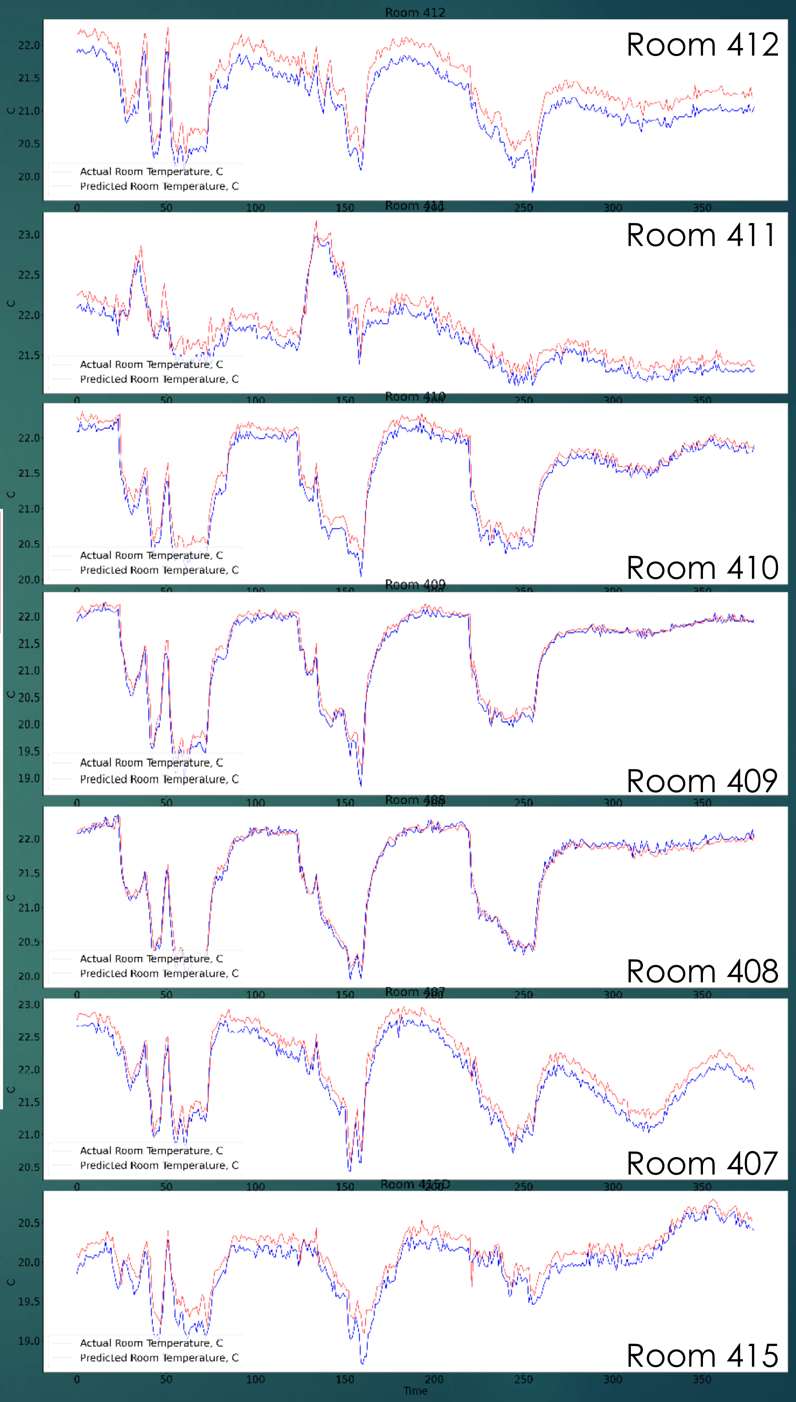
MLP Algorithm: Single-Output (S-O) vs. Multi-Outputs (M-O)



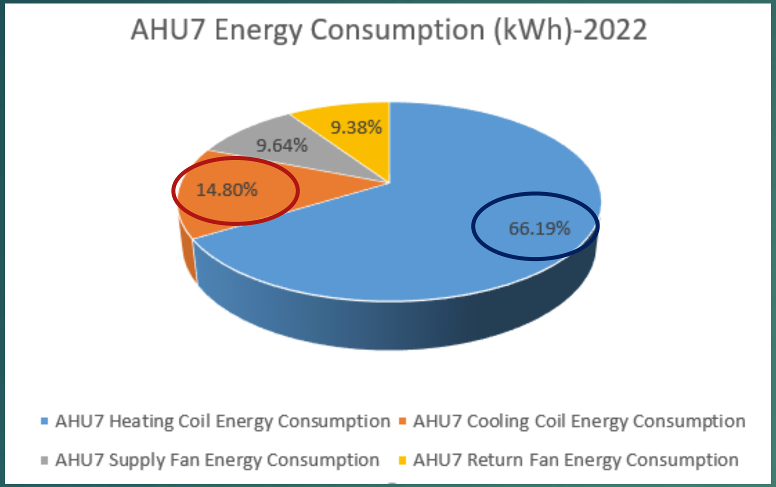


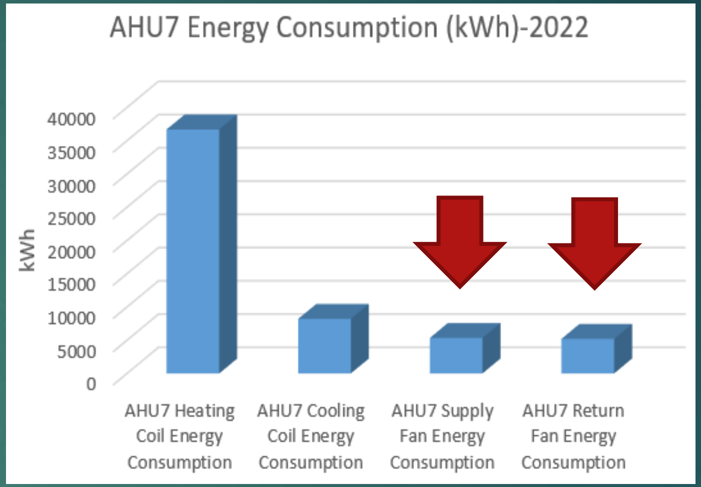
Evaluation of Model Accuracy by Implementation of New Set Points on Actual HVAC System

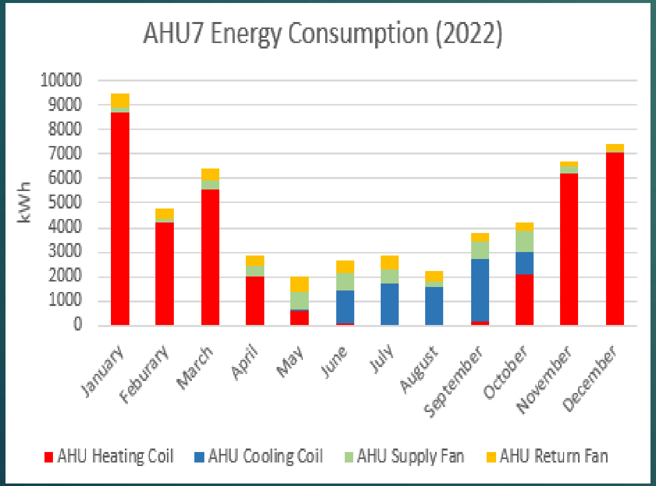
Zones	MLP (with new set points)			MLP (with test dataset in modeling steps)		
	MSE	RMSE	MAE	MSE	RMSE	MAE
Room 412	0.080	0.283	0.267	0.031	0.176	0.123
Room 411	0.027	0.167	0.141	0.031	0.176	0.134
Room 410	0.026	0.161	0.131	0.030	0.173	0.121
Room 409	0.022	0.149	0.104	0.033	0.181	0.125
Room 408	0.009	0.097	0.073	0.015	0.122	0.092
Room 407	0.040	0.200	0.178	0.026	0.161	0.112
Room 415	0.032	0.181	0.151	0.026	0.161	0.118

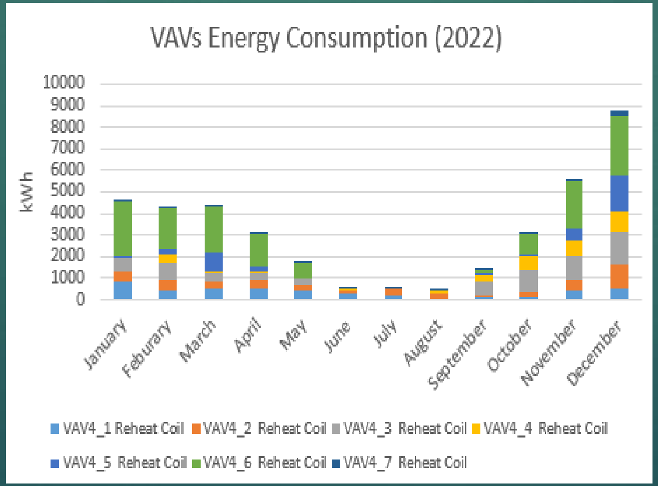


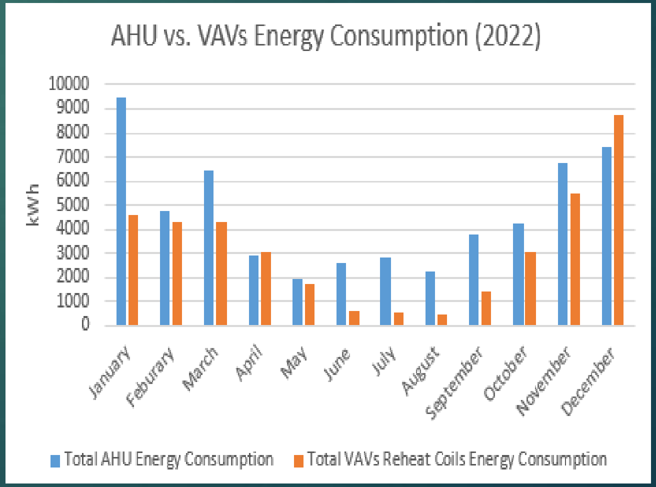
HVAC System Energy Consumption Assessments-2022





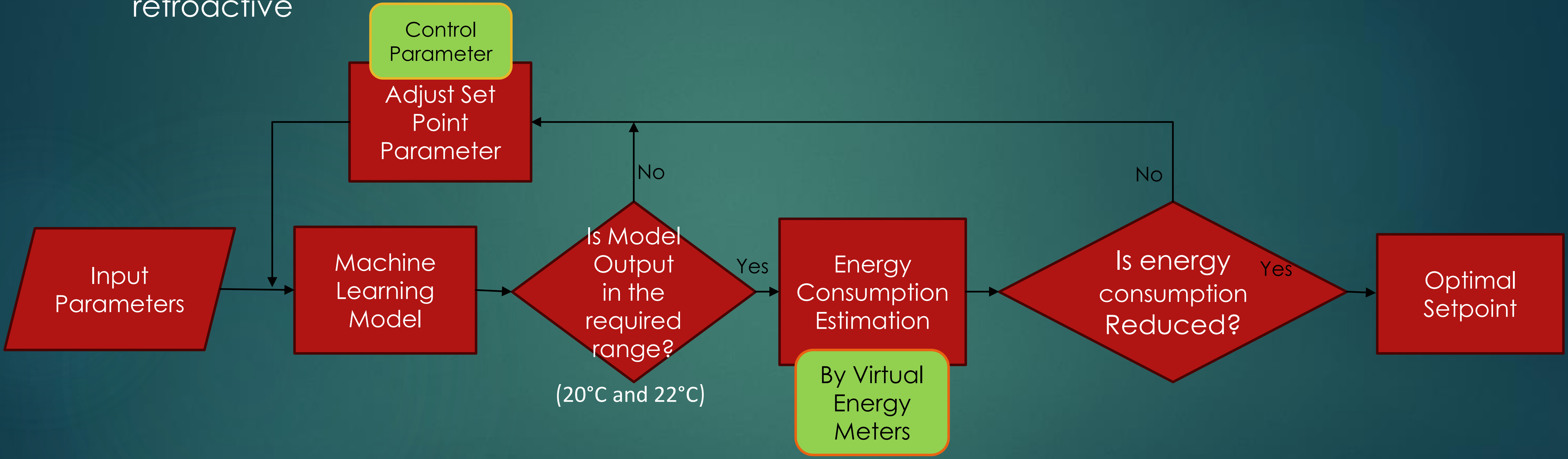






Optimization Process

- The energy consumption data was created based on defined virtual energy meters, which are retroactive



Heating Coils Energy Optimization

Energy consumption of AHU7_HC before and after optimization.

Month	Energy Consumption Heating Coil of AHU7 (kWh) in 2022 BEFORE optimization	Energy Consumption Heating Coil of AHU (kWh) in 2022 AFTER optimization	Energy Consumption Reduction (%)
January	8734.39	8019.23	8.19%
February	4179.57	3844.15	8.03%
March	5559.74	4869.37	12.42%
April	1984.98	1843.29	7.14%
May	559.77	555.60	0.74%
June	80.91	80.90	0.01%
July	34.83	34.83	0%
August	6.24	6.24	0.00%
September	179.43	177.28	1.20%
October	2059.25	1859.99	9.68%
November	6213.65	5540.49	10.83%
December	7088.05	6544.31	7.67%
Total Energy Consumption	36680.85	33375.75	9.01%

Energy consumption of VAV4_6 reheat coil before and after optimization.

Month	Energy Consumption Reheat Coil of VAV4_6 (kWh) in 2022 BEFORE optimization	Energy Consumption Reheat Coil of VAV4_6 (kWh) in 2022 AFTER optimization	Energy Consumption Reduction (%)
January	2569.97	2354.18	8.40%
February	1891.18	1741.99	7.89%
March	2112.12	1927.41	8.75%
April	1544.31	1429.55	7.43%
May	705.17	656.05	6.97%
June	12.40	11.45	7.63%
July	0	0	0.00%
August	0	0	0.00%
September	229.77	215.87	6.05%
October	921.75	849.46	7.84%
November	2170.30	1980.66	8.74%
December	2759.44	2534.79	8.14%
Total Energy Consumption	14916.44	13701.45	8.15%

Conclusion

- The primary goal of this study was to suggest the most accurate data-driven model for HVAC systems.
  - Feature selection techniques were applied to determine the most critical features.
  - Tree-based and deep-learning algorithms modeling performance were analyzed.
  - This study proved that the multi-outputs deep learning algorithms produced better outcomes.
  - The MLP algorithm was the best algorithm with an average RMSE of 0.16 °C.
- The secondary goal of this study was energy optimization of HVAC systems based on the proposed model.
  - The objective was to determine the optimal supply air temperatures of HVAC system.
  - The energy optimization process of heating coils produced the best settings for the supply air temperatures
  - Result in reducing the energy consumption about 9%.

Further Work

EXPLORING THE UTILIZATION OF OCCUPANCY AND CO_2 DATA TO OPTIMIZE HVAC SYSTEM OPERATION.

THE PRACTICAL APPLICABILITY AND EFFECTIVENESS OF THE PROPOSED IDEAS.

REAL-WORLD VALIDATION AND PERFORMANCE TESTING.

LONG-TERM MONITORING OF THE PROPOSED MODEL AND ENERGY OPTIMIZATION.

Publications

- Norouzi P., Maalej S., Mora R. Applicability of Deep Learning Algorithms for Predicting Indoor Temperatures: Towards the Development of Digital Twin HVAC Systems. Buildings. 2023; 13(6):1542. https://doi.org/10.3390/buildings13061542
- Norouzi P., Maalej S., and Mora R. Development of data-driven modeling and energy optimization of HVAC system. *(Under Review)*.

Thank you!

References

[1] Report, "Energy Fact Book," Natural Rsources Canada, 2021.

[2] Report, "Energy Efficiency Trend in Canada," 2011.

[3] Schein J., Bushby ST., Castro NS., House JM., "A rule-based fault detection method for air handling units.," Building Energy, 2012.

[4] Rios Moreno GJ., Trejo-Perea M., Castaneda Miranda R., Hernandez Guzman VM., Herrera-Ruiz G., "Modeling temperature in intelligent buildings by means of autoregressive models," 2007.

[5] Pérez Lombard, Ortiz J., Pout C., "A review on building energy consumption information.," *Energy and Buildings,* Vols. 40, No. 3, pp. 394-398, 2008.

[6] Datong P. Zhou, Qie Hu, and Claire J. Tomlin,, "Quantitative Comparison of Data-Driven and Physics-Based Models for Commercial Building HVAC Systems,," in American Control Conference, 2017.

[7] Kusiak A, Tang F, Xu G., " Multi-objective optimization of HVAC system with an evolutionary computation algorithm.," Energy, 2011.

[8] F. Tang, A. Kusiak, X. Wei, , "Modeling and short-term prediction of HVAC system with a clustering algorithm,," 2014.

[9] Chakraborty, D., & Elzarka, H., " Early detection of faults in HVAC systems using an XGBoost model with a dynamic threshold.," Energy & Buildings, vol. 185, pp. 326-344, 2019.

[10] Kusiak A, Tang F, Xu G., " Multi-objective optimization of HVAC system with an evolutionary computation algorithm.," Energy, 2011.

[11] A. E. Ben-Nakhi and M. A. Mahmoud,, " Energy conversation in buildings through efficient A/C control using neural netowrks," Applied Energy,, vol. 73, pp. 5-23, 2002.

[12] F. Tang, A. Kusiak, X. Wei, , "Modeling and short-term prediction of HVAC system with a clustering algorithm,," 2014.

[13] A. Kusiak, G. Xu, F. Tang, , "Optimization of an HVAC system with a strength multi-objective particle-swarm algorithm,," Energy , 2011.

[14] A. Kusiak, M. Li, F. Tang,, " Modeling and optimization of HVAC energy consumption," Applied Energy,, vol. 87, pp. 3092-3102, 2010.