Application of Artificial Intelligence in Heating, Ventilation, and Air Conditioning (HVAC) systems for energy efficiency and cost reduction

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Abstract

Urbanization has led to a sharp rise in the demand for power over the past 10 years, alarmingly rising greenhouse gas (GHG) emissions. HVAC (heating, ventilation, and air conditioning) systems account for nearly half of the energy used by buildings, and minimizing the energy use of the HVAC systems is essential. In the light of progress in building intelligence and energy technologies, traditional methods for HVAC optimization, control, and fault diagnosis will struggle to meet essential requirements such as energy efficiency, occupancy comfort and reliable fault detection. Machine learning and data science have great potential in this regard, particularly with developments in information technology and sensor equipment, providing access to large volumes of high-quality data.

Step 1: Prototype Selection

1.0 Introduction

1.1 Problem Statement

Energy is the most important component for the operation of various sectors, including transportation, business, residential buildings, and many others. Recent technological developments have led to a sharp rise in global energy consumption, which is alarmingly increasing the rate of greenhouse gas emissions. As shown in Fig 1, the world energy consumption by different sources of fuels was about 173,340 Terra-Watt-Hr (TWh) in 2019, while it was 122,073 TWh in 2000. The world's energy consumption increased by approximately 42% within 19 years. Electricity is the prime energy source that the built environment utilizes.

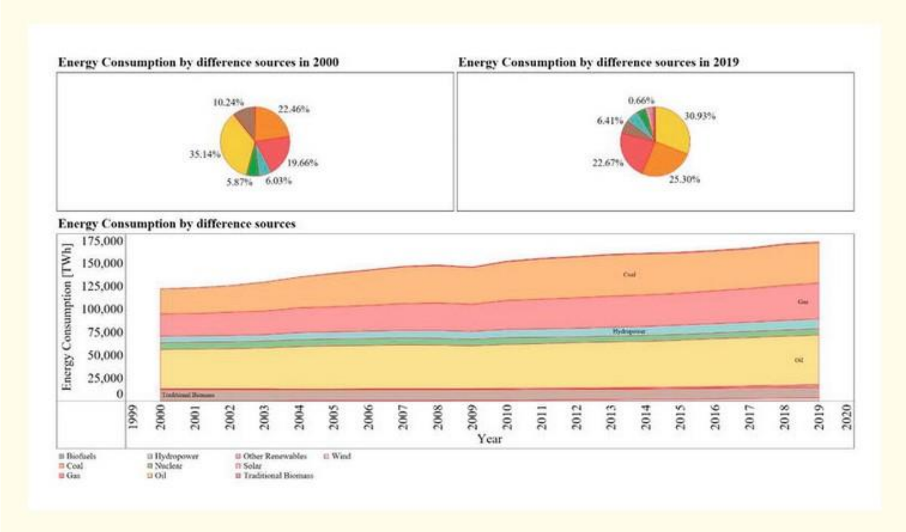


Fig 1. Energy consumption by different fuel sources since 2000

Global electricity generation in 2021 increases approximately twofold compared to 2000 to accommodate the drastic increase in energy consumption in the built environment, as indicated in Fig 2. Primary fuel sources, like coal and gas, account for almost 60% of total primary energy sources, whereas renewable energy makes up only 13% of total primary energy sources. IEA reported that the increase in coal-fired power plants contributes to a sharp rise in carbon dioxide emissions. The electricity demand continues to grow by 4% in 2022. Despite substantial expansions of renewable energy usage, it is anticipated to offset the rise only partially in electricity consumption. Due to the rise of greenhouse gas emissions, the environment is seriously threatened by the continued growth of energy consumption.

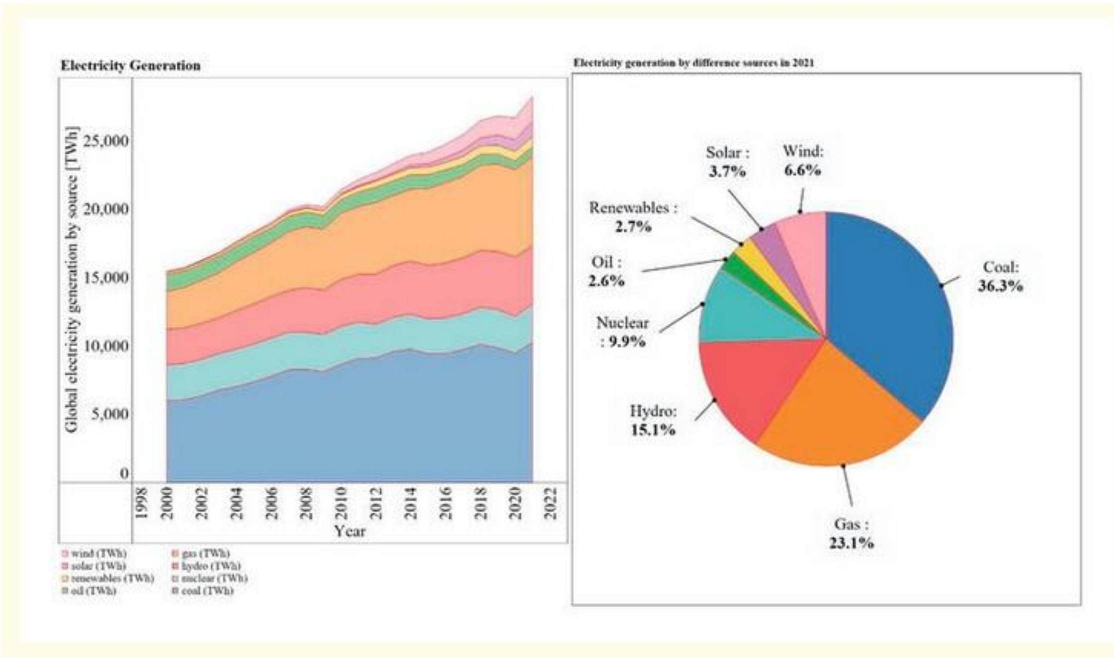


Fig 2. Global electricity generation by sources from 2000 to 2021

2.0 Market/Customer/Business Need Assessment

2.1 Need for AI in HVAC

- **Poor Building Envelope**: Commercial buildings with poor insulation, inefficient windows, or leaky roofs require more energy to regulate indoor temperature and humidity. The building envelope is the physical barrier between the interior and exterior of the building, and if it is not well-maintained, it can result in higher energy consumption.
- **Outdated HVAC Systems**: Many commercial buildings still rely on obsolete HVAC systems, which lack energy efficiency features, such as variable speed drives, intelligent controls, and automation. These systems can result in energy wastage, high energy bills, and poor occupant comfort.
- **Occupancy Patterns**: Commercial buildings have varying occupancy patterns, and traditional HVAC systems are not designed to adjust to these patterns effectively. Inefficient systems can result in heating, cooling, and ventilating unoccupied spaces, leading to energy wastage.
- **Lack of Energy Management Systems**: Many commercial buildings lack proper energy management systems, resulting in unmonitored energy use and no way to track and reduce energy consumption. Without adequate energy management, it is challenging to identify inefficiencies in the building's systems and address them effectively.

2.2 How AI can optimize HVAC energy consumption

- **Intelligent Control and Automation**: AI-powered HVAC systems can automate the regulation of temperature, humidity, and air quality in real time based on occupancy patterns, weather conditions, and other variables. With intelligent controls and machine learning algorithms, HVAC systems can adjust their operations to optimize energy usage and reduce wastage.
- **Predictive Maintenance**: AI-powered HVAC systems can detect and predict maintenance issues before they become costly problems. HVAC systems can predict failures, optimize performance, and reduce downtime by analyzing sensor data and other sources.
- **Energy Consumption Analytics**: AI-powered analytics can provide insights into energy usage patterns, identifying areas where energy consumption can be reduced. HVAC systems can use these insights to optimize operations and reduce energy consumption.
- **Improved Occupant Comfort**: AI-powered HVAC systems can learn occupant preferences and adjust their operations to provide optimal comfort while minimizing energy usage. Intelligent systems can detect changes in occupancy and adjust their settings accordingly, ensuring that energy is not wasted on unoccupied spaces.
- **Energy Efficiency**: AI algorithms can analyze real-time data such as occupancy patterns, weather forecasts, and building orientation to optimize the HVAC system's performance, thereby reducing energy consumption and costs.

- **Reduced Carbon Footprint**: AI-integrated HVAC systems can help reduce a building's carbon footprint by optimizing energy consumption, contributing to a more sustainable environment.

4.0 External Searches

4.1 AI learning algorithm classifications

AI machine learning is classified into supervised, semi- supervised, unsupervised, deep and reinforced learning depending on the data type (continuous, discrete, qualitative, quantitative) and task requirement. Supervised learning algorithms are better suited for classification and regression problems due to their prediction and modelling accuracies. In contrast, unsupervised learning algorithms are suitable for clustering problems. The need for superior advantages to supervised and unsupervised learning algorithms led to the development of semi-supervised learning. Thus, it enables the mapping of labelled and unlabelled data.

In reinforced learning, optimal steps towards the target goal depend on previous training environment consequences. Deep learning combines initialization of weights and biases using unsupervised learning and backpropagation tuning algorithms. Most AI learning algorithms can minimize error functions (or loss function, cost function) by accurately tracking the global optimal parameters through optimization techniques (like swarm particle optimization, simplex, support vector machines, and visualization monitoring of gradient descent, batch gradient descent, stochastic gradient descent, mini gradient descent).

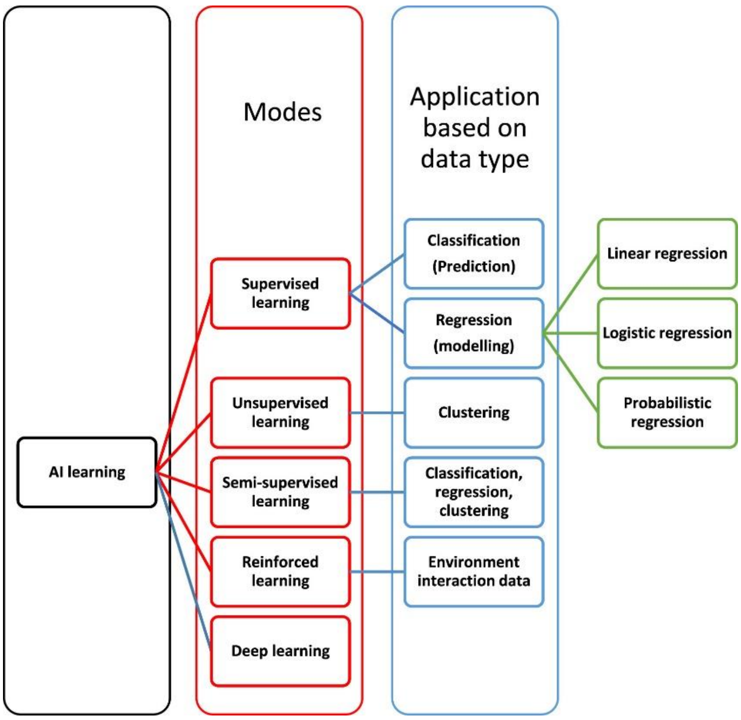


Fig 3. AI learning algorithm classifications

8.0 Applicable Constraints

8.1 Key challenges and constraints of AI-integrated HVAC systems:

- **Data Quality**: The effectiveness of AI algorithms depends on the data quality used to train them. Inaccurate or incomplete data can lead to inaccurate predictions and suboptimal system operations.
- **System Complexity**: Integrating AI technology with HVAC systems can add complexity to the system, making it harder to design, install, and maintain. This complexity can lead to higher costs, longer installation times, and increased maintenance requirements.
- **Cybersecurity**: As with any connected technology, AI-integrated HVAC systems are vulnerable to cybersecurity threats like hacking and data breaches. This requires robust cybersecurity measures to protect building systems and occupants.
- **Regulatory Compliance**: Building codes and regulations can limit the use of certain AI technologies, making it harder to implement them in some buildings.
- **Cost**: Implementing AI-integrated HVAC systems can require a significant upfront investment, which may challenge some building owners and managers.
- **Limited Compatibility**: Not all HVAC systems are compatible with AI technology, and retrofitting older systems can be challenging and costly. This can limit the ability of some buildings to benefit from AI-integrated HVAC systems.

11.0 Concept Development

11.1 Input-output model of HVAC system

As shown in Fig 4, an HVAC system has three inputs—power, external heat gain, and internal heat gain. The output is the indoor temperature control results. The external heat comes from the heat transfer caused by the outside weather to the building. The internal heat is generated by the entry and exit of indoor personnel and the waste heat of indoor equipment. The HVAC system adds or moves heat Q'_{hvac}, from the building interior via power input. The idea is to control the indoor temperature control to the set point. In this process, any HVAC system that consumes the least power under the same temperature control profile is the most energy-efficient HVAC system.

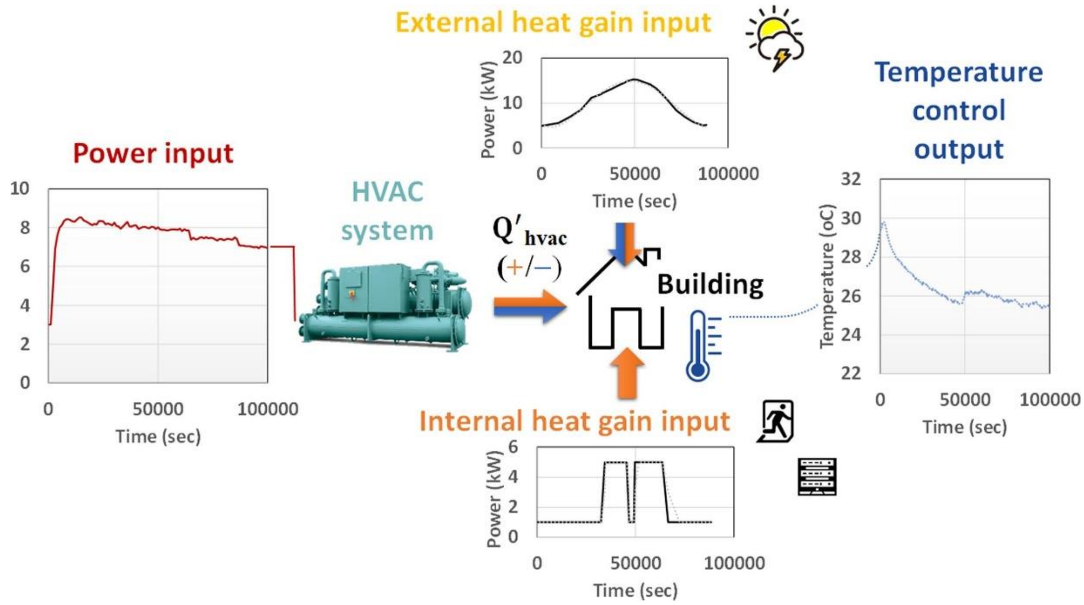


Fig 4. Input-output model of HVAC systems

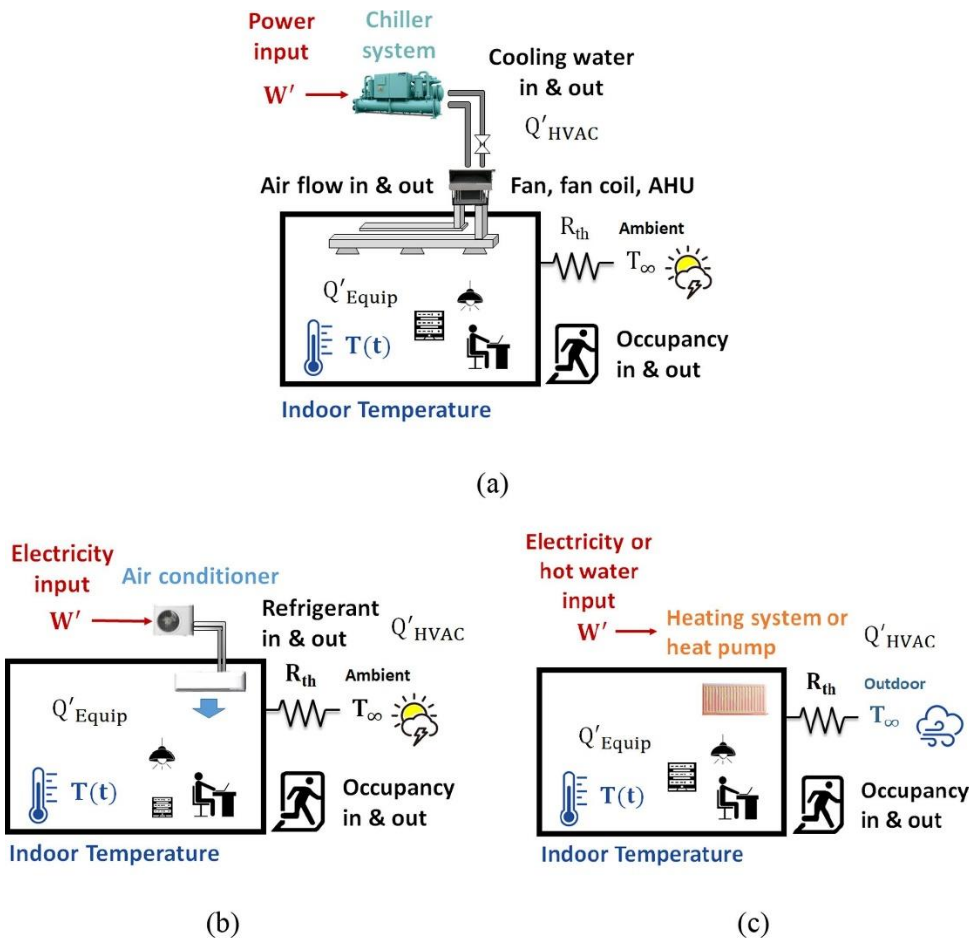


Fig 5. Input-output models for four different HVAC systems: (a) Chiller system and AHU, fan, and fan coils; (b) air conditioner; and (c) heating system or heat pump

11.2 AI Models for HVAC systems

11.2.1 ANN-based modelling and model-based predictive control (collectively referred to as "MPC")

Artificial neural networks (ANNs), also known as biological neural networks, are the most widely used AI models in HVACs. ANNs process information using neuron relationship modelling of inputs to outputs. ANNs behaves like black boxes equipped with interconnected processing units (that is, neurons). ANN neurons receive process, and send transformed signals between each other using mathematical functions that could be activation, summation or transfer functions. Arrangement of neurons is according to layers, namely, input layer(s), output layer(s) and probably hidden layers. Artificial neural network (ANN) models deliver output(s) from input(s) through sets of computational processing units and predefined activation functions within neurons. ANN neurons identification depends on selected activation or transfer functions. ANN models' performance depends on the number of hidden layers, number of hidden layer neurons, selection of training algorithms, activation function characteristics and error parameters.

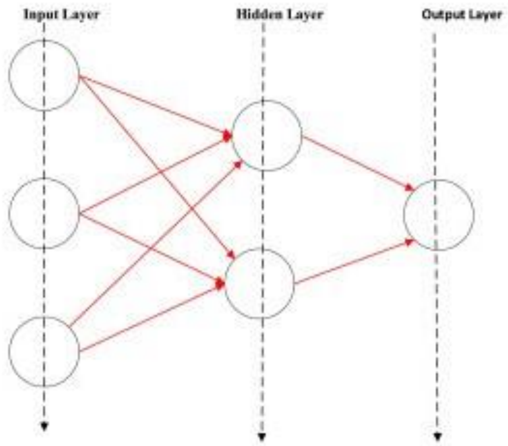


Fig 6. Feedforward backpropagation neural network

11.2.2 Feedforward neural network

Feedforward neural network allows unidirectional flow of signals from inputs to output without signal cycling or loop. These networks, like multilayer perceptron networks, are universal approximators for linear regression functions. Universal approximation functions give accurate gradient information between inputs and outputs. The outputs of neural networks are the summation of weights, biases and inputs. The primary characteristics of universal approximation feedforward neural networks are the application of non-polynomial activation functions and linear outputs. Feedforward neural networks are better suited for either classification or regression problems. Feedforward neural networks train to set their weights and biases parameters using different backpropagation techniques (Feedforward backpropagation, Cascade backpropagation and Elman backpropagation).

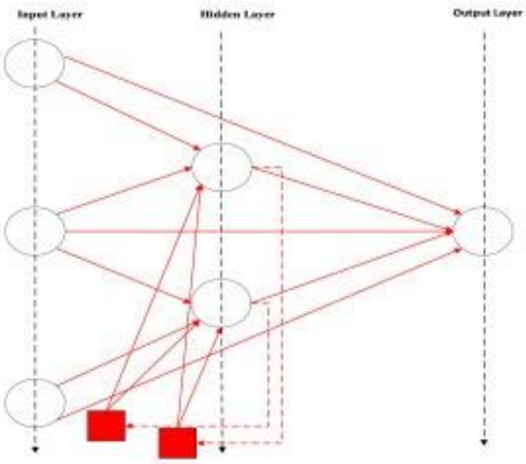


Fig 7. Elman backpropagation neural network

11.2.3 Adaptive neuro-fuzzy inference system (ANFIS)

Adaptive neural fuzzy inference system (ANFIS) is a development introduced to fuzzy logic techniques for improved performance in engineering applications. In fuzzy systems, inputs are processed using predefined fuzzy arithmetic and rules to give output(s). Thus, Fuzzy systems have better reasoning capacity while neural networks have improved learning ability. Two types of adaptive inference systems based on fuzzy rules (Mamdani and Sugeno type) are adapted for engineering applications.

- In the **Mamdani** adaptive neuro-fuzzy system, the membership functions are fuzzy in nature. Mamdani ANFIS rules are more intuitive and interpretable than Sugeno ANFIS. It is more applicable to single output based functional analysis.
- **Sugeno** has linear or constant membership functions that enhance simplicity and accuracy. Sugeno ANFIS are better suitable for multiple outputs based on computational analysis.

Step 2: Prototype Development

12.0 Final Product Prototype

The final product will be a product/service (depending on the business model), that will seamlessly connect with the user's HVAC systems and resolve common thermal comfort issues such as overcooling and undercooling. The AI model will take in user's input data (features like temperature, humidity, CO_2 emission, energy consumption etc.) and automatically change its heat output depending on the outside variables. This adaptability will not only provide a better user experience but also help in reducing CO_2 emissions and thereby reducing the energy consumption. By using our product, small businesses that rent their workplaces can save millions of dollars, reducing their costs significantly.

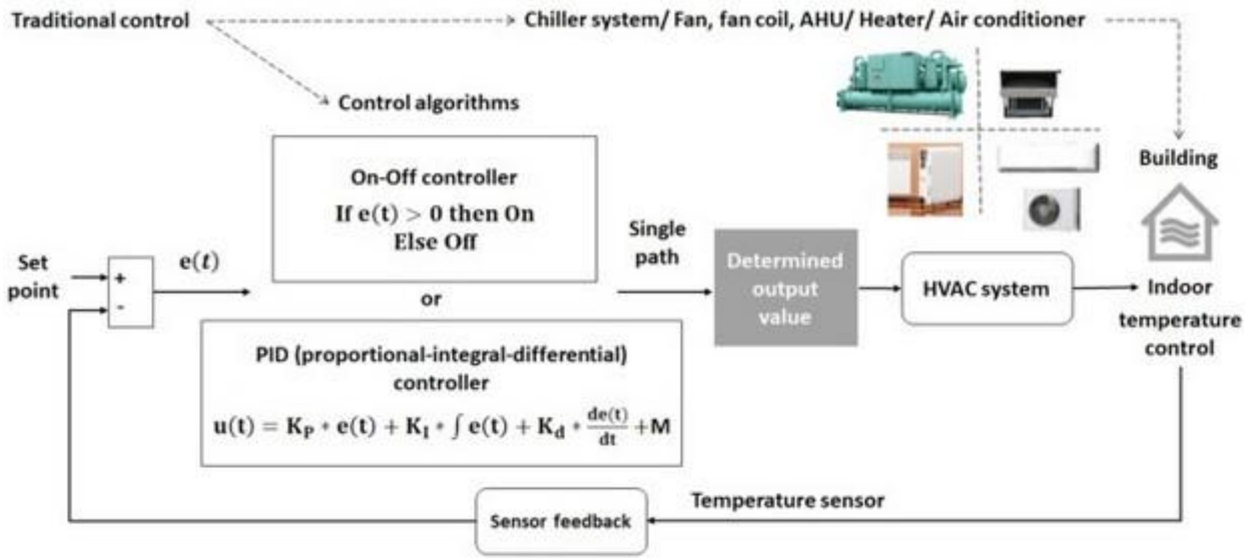


Fig 8. On-Off or PID controller for the traditional HVAC system

The most effective AI model – MPC (ANN based modelling)

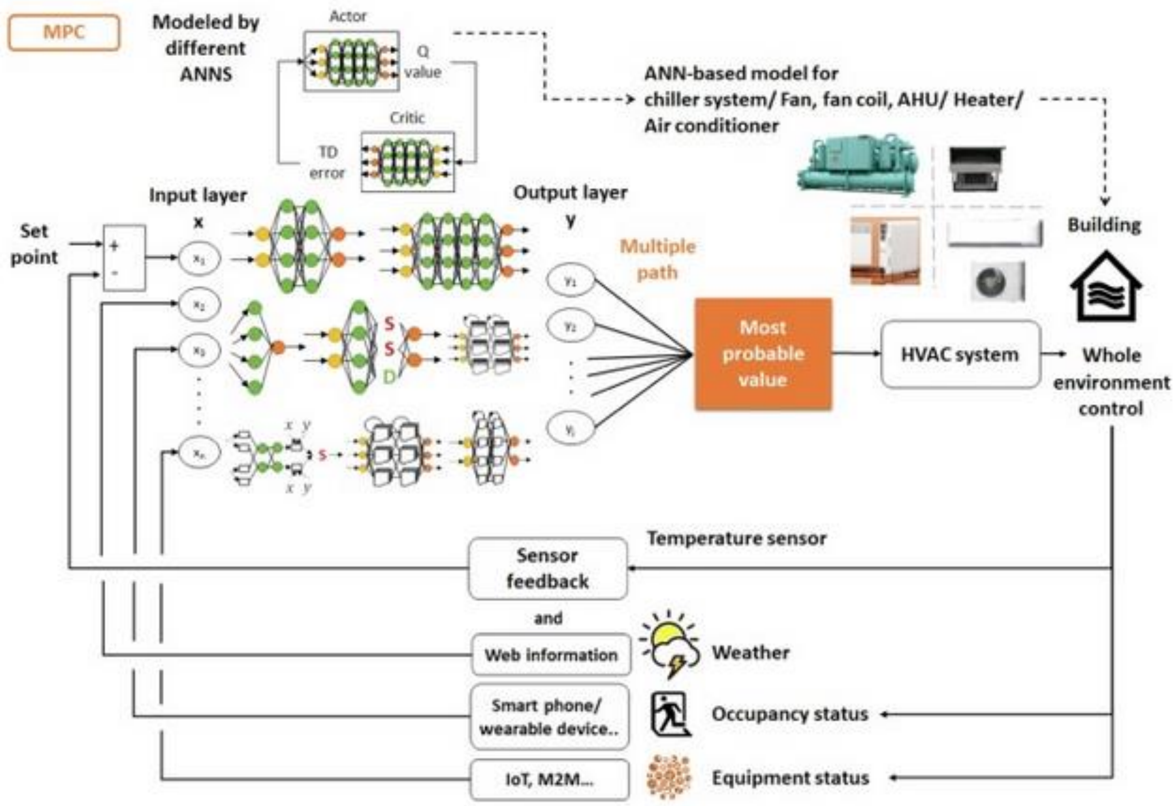


Fig 9. MPC for an AI-enabled energy-efficient HVAC system

14.0 Code Implementation

Csv dataset for code implementation – [Kaggle]

Code implementation – [GitHub link]

For the code implementation, I have used a simple Multivariate regression algorithm to predict the energy consumption for an average HVAC user. Regression algorithm is not the best model when it comes to predict values with multiple features, but nevertheless it does a pretty descent job in predicting outcomes. From the dataset, I found a direct correlation between temperature and energy consumption (Fig 16). As the temperature goes up, energy consumption also goes up. While training data using regression, r-squared value comes out to be 0.6, which is not great but not bad either. The model's prediction for the energy consumption for an average HVAC user was around 80KWh (Fig 22).

14.1 Exploratory Data Analysis

```
[7]  data.info()

<class 'pandas.core.frame.DataFrame'>
Index: 1000 entries, 2022-01-01 00:00:00 to 2022-02-11 15:00:00
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Temperature        1000 non-null   float64
 1   Humidity           1000 non-null   float64
 2   SquareFootage      1000 non-null   float64
 3   Occupancy          1000 non-null   int64
 4   HVACUsage          1000 non-null   object
 5   LightingUsage      1000 non-null   object
 6   RenewableEnergy    1000 non-null   float64
 7   DayOfWeek          1000 non-null   object
 8   Holiday            1000 non-null   object
 9   EnergyConsumption  1000 non-null   float64
dtypes: float64(5), int64(1), object(4)
memory usage: 85.9+ KB
```

Fig 10. Csv dataset info

```
[10] data.describe()
```

	Temperature	Humidity	SquareFootage	Occupancy	RenewableEnergy	EnergyConsumption
count	1,000.00	1,000.00	1,000.00	1,000.00	1,000.00	1,000.00
mean	24.98	45.40	1,500.05	4.58	15.13	77.06
std	2.84	8.52	288.42	2.87	8.75	8.14
min	20.01	30.02	1,000.51	0.00	0.01	53.26
25%	22.65	38.30	1,247.11	2.00	7.63	71.54
50%	24.75	45.97	1,507.97	5.00	15.07	76.94
75%	27.42	52.42	1,740.34	7.00	22.88	82.92
max	30.00	59.97	1,999.98	9.00	29.97	99.20

Fig 11. Descriptive Statistics

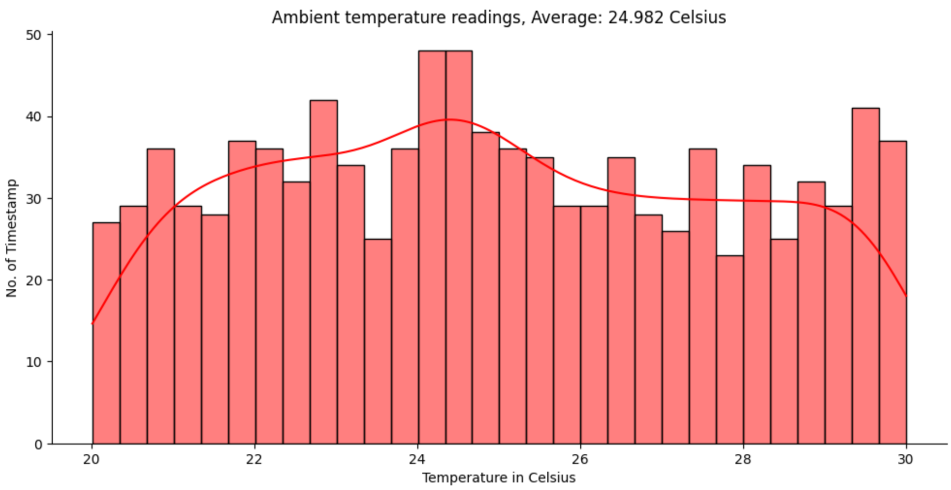


Fig 12. Ambient Temperature readings

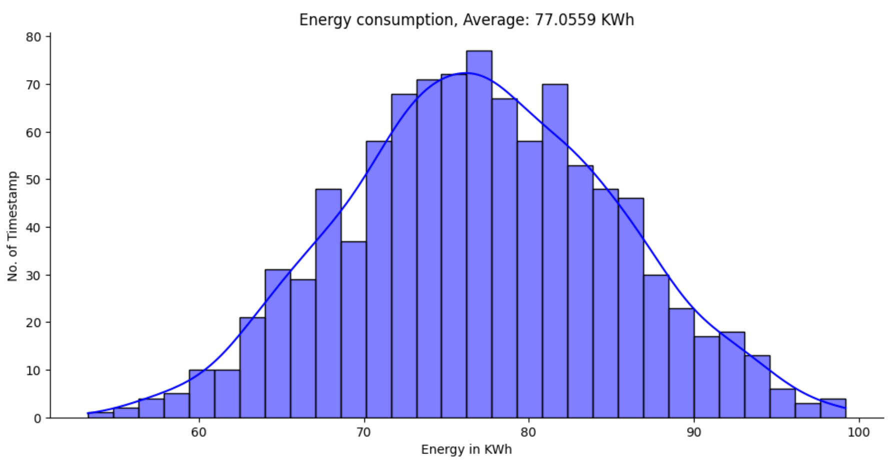


Fig 13. Energy consumption

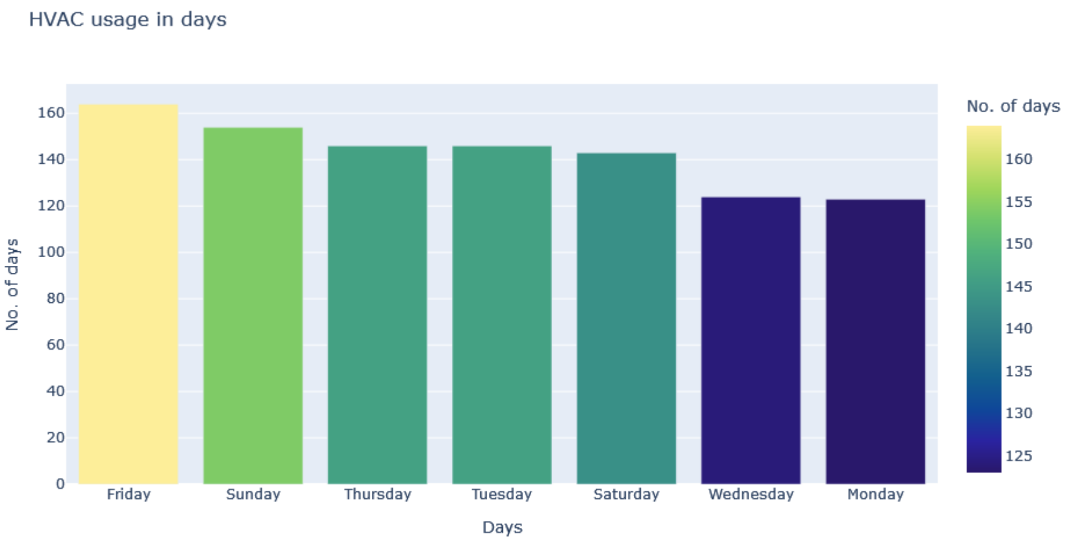


Fig 14. HVAC usage in days

14.2 Understanding relationship between data

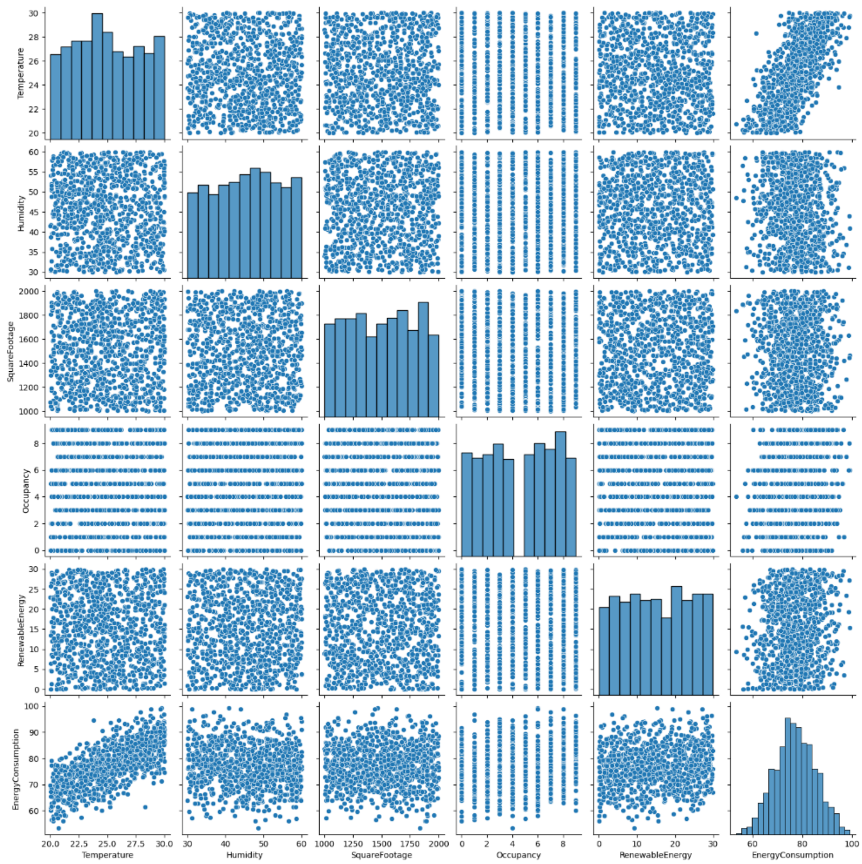


Fig 15. Relationship between features

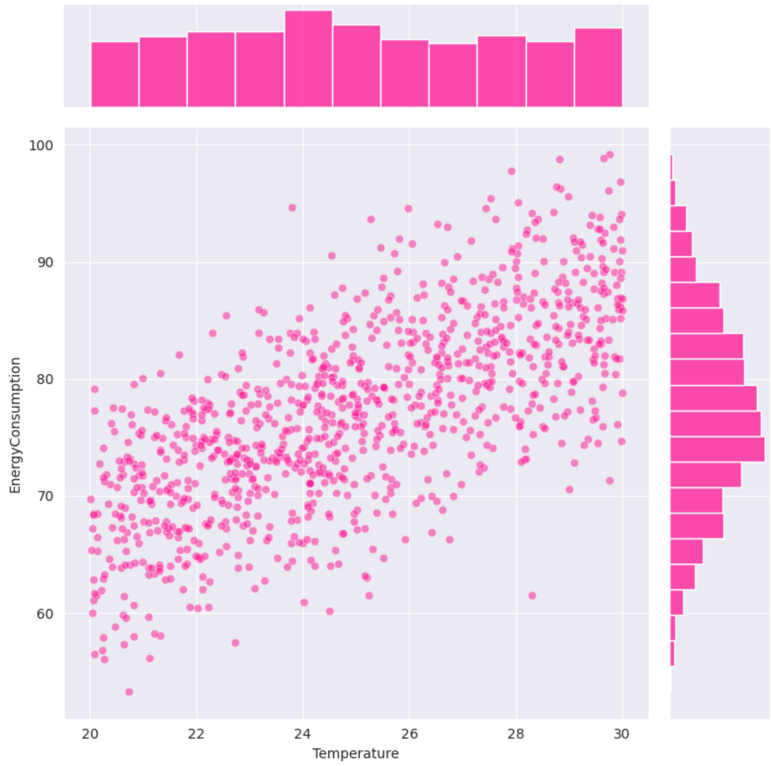


Fig 16. Relationship between Temperature and Energy consumption

14.3 Split training

Split training and Test dataset

```
[43] new_df = data[data["HVACUsage"] == "On"]

     target = new_df["EnergyConsumption"]
     features = new_df.drop(["EnergyConsumption", "HVACUsage", "LightingUsage", "Holiday", "DayOfWeek"], axis=1)

     X_train, X_test, y_train, y_test = train_test_split(features,
                                                         target,
                                                         test_size=0.2,
                                                         random_state=10)
```

```
[44] # % of training set
     train_pct = 100*len(X_train)/len(features)
     print(f'Training data is {train_pct:.3}% of the total data.')

     # % of test data set
     test_pct = 100*X_test.shape[0]/features.shape[0]
     print(f'Test data makes up the remaining {test_pct:0.3}%.')
```

```
Training data is 79.9% of the total data.
Test data makes up the remaining 20.1%.
```

Fig 17. Splitting dataset for Multivariate Regression

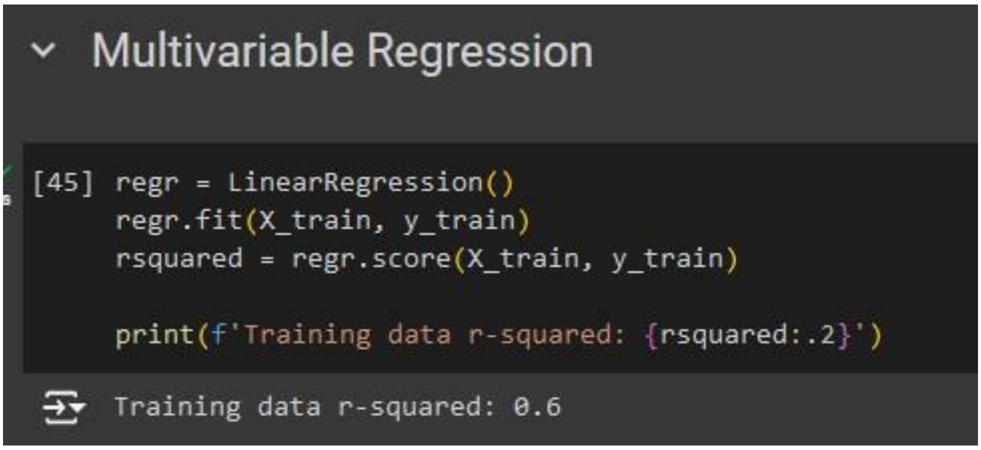


Fig 18. R-squared value

14.4 Actual vs Predicted values and Residual Skewness

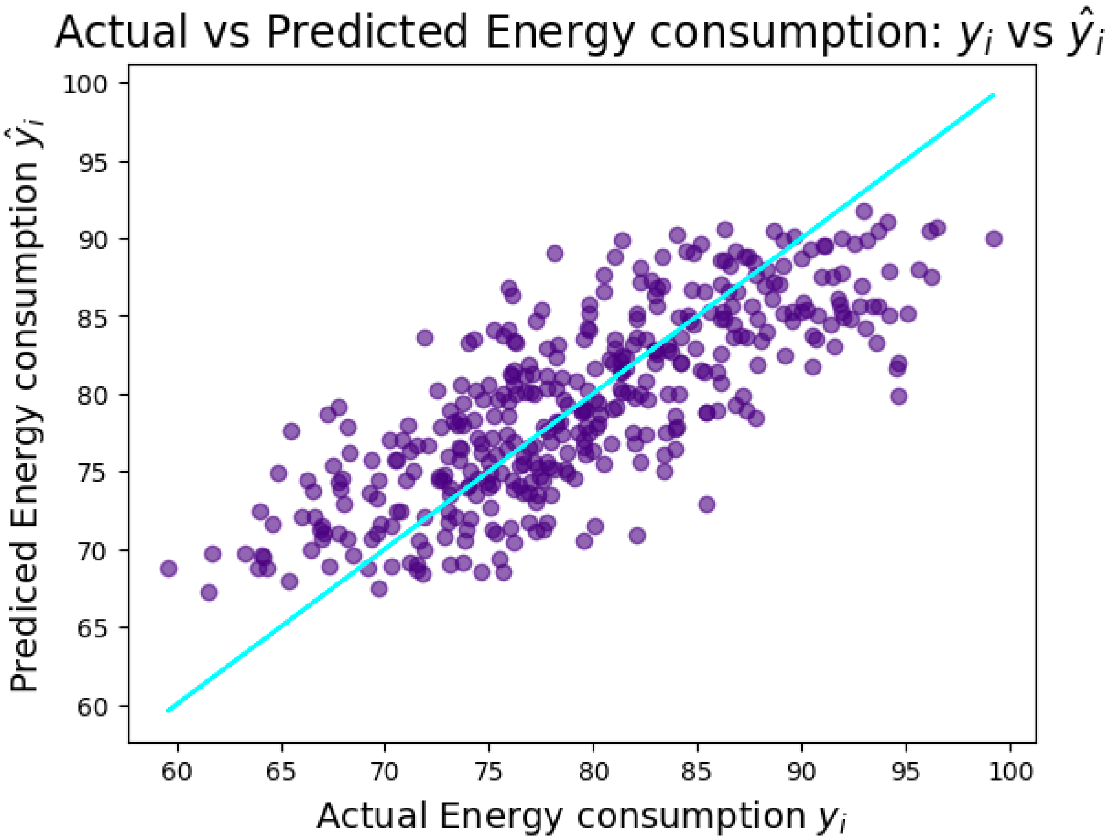


Fig 19. Actual vs Predicted Energy values

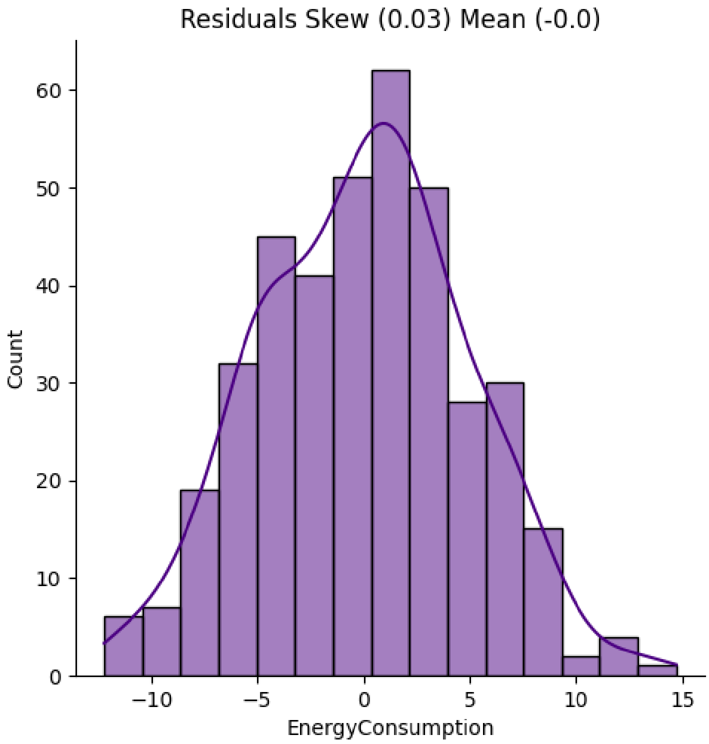


Fig 20. Residual distribution chart

14.4 Predicting energy consumption using Multivariate Regression

$$\hat{EnergyConsumption} = \theta_0 + \theta_1 Temperature + \theta_2 Humidity + \theta_3 SquareFootage + \theta_4 Occupancy + \theta_5 RenewableEnergy$$

Fig 21. Energy consumption prediction using Regression coefficient

```
# Make prediction
estimate = regr.predict(energy_stats)[0]
print(f'The energy estimate is {estimate}KWh')
```

```
The energy estimate is 79.4898849899327KWh
```

Fig 22. Energy estimate for an average HVAC user

Step 3: Business Modelling

9.0 Business Model

9.1 B2B model

In B2B model, we will provide services to major HVAC manufacturers (LG, Daikin, Voltas, Bluestar etc.). Since these manufacturers occupy majority of HVAC market, it will be easier to integrate AI with outdated HVAC systems

9.2 B2C model

In B2C model, we will directly reach out to customers who wants to seamlessly connect their HVAC systems in one place.

Step 4: Financial Modelling

Csv dataset for code implementation – [US Govt data]

Code implementation – [GitHub link]

HVAC Market Share by Efficiency and Capacity: Beginning 2017 dataset is based on heating, ventilation, and air conditioning (HVAC) sales data reported to D+R International by Heating, Air-conditioning & Refrigeration Distributors International (HARDI) members participating in the Unitary HVAC Market Report. Participation in the report is voluntary for distributors. The dataset covers New York State and the Northeast (includes Maine, New Hampshire, Vermont, Massachusetts, Connecticut, and Rhode Island). Blank cells represent data that are not currently available.

Viability, Feasibility and Monetization

```
data = pd.read_csv("hvac_sales.csv", index_col=0)
data.head()
```

Year	Region	Type	Units	AFUE	SEER	Ducted	Refrigerant	Cooling (Btu/hr)	Heating (Btu/hr)	MotorType	HSPF	FinalEstimate	EER	FuelType
2021	Northeastern	AC	33	NaN	13.00	0.00	410.00	18,000.00	NaN	NaN	NaN	165.00	NaN	NaN
2021	Northeastern	AC	326	NaN	13.00	0.00	410.00	24,000.00	NaN	NaN	NaN	1,631.00	NaN	NaN
2021	Northeastern	AC	289	NaN	13.00	0.00	410.00	30,000.00	NaN	NaN	NaN	1,446.00	NaN	NaN
2021	Northeastern	AC	31	NaN	13.00	0.00	410.00	42,000.00	NaN	NaN	NaN	155.00	NaN	NaN
2021	Northeastern	AC	49	NaN	13.00	0.00	410.00	48,000.00	NaN	NaN	NaN	245.00	NaN	NaN

Fig 23. HVAC sales dataset (US)

Sales by Year

```
[10] sales_by_year = data.groupby("Year")["Units"].sum()
     sales_by_year.head()
```

```
Year
2017    116056
2018    138297
2019    136458
2020    108060
2021    129324
Name: Units, dtype: int64
```

```
[11] fig = px.bar(x=sales_by_year.index, y=sales_by_year.values,
                  color=sales_by_year.values,
                  color_continuous_scale=px.colors.sequential.Sunsetdark,
                  title="HVACs sales by Year - NY and Northeastern region (USA)", labels={"color" : "No. of HVACs sold"}, text_auto=Tr

     fig.update_layout(xaxis_title="Years", yaxis_title="No. of HVACs sold")
     fig.show()
```

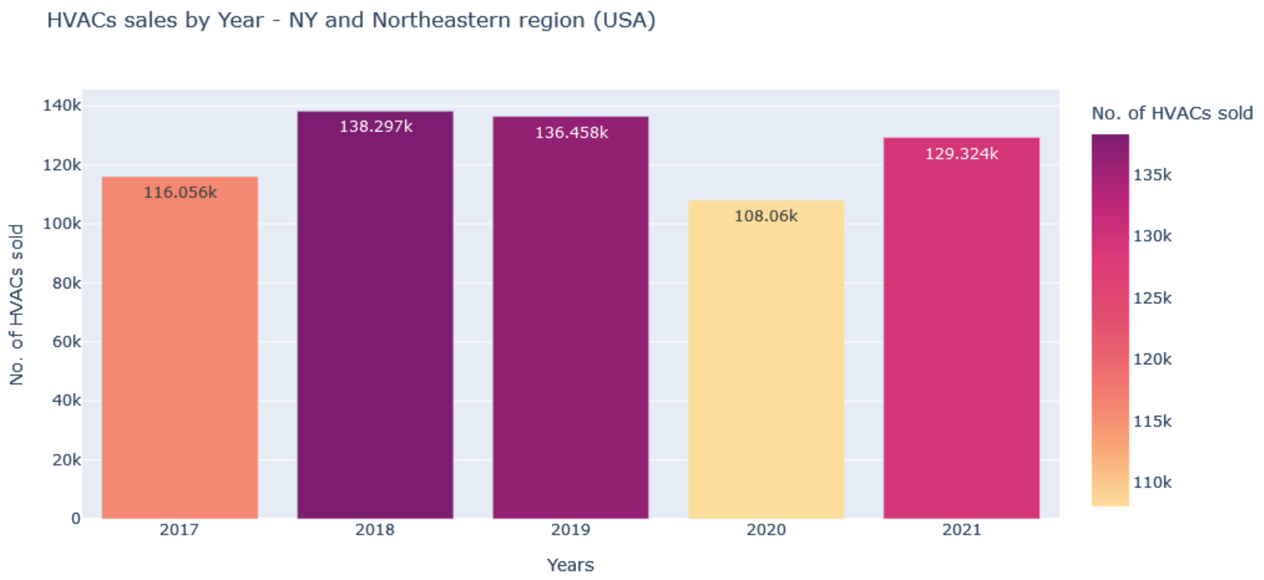


Fig 24. Sales by years (2017 - 2021)

From the above data, it is evident that the HVAC market is a viable option investing in, due to the high market demand. In 2020, sales of HVAC reduced due to the Covid-19 pandemic, but in 2021 it rapidly picked it’s pace.

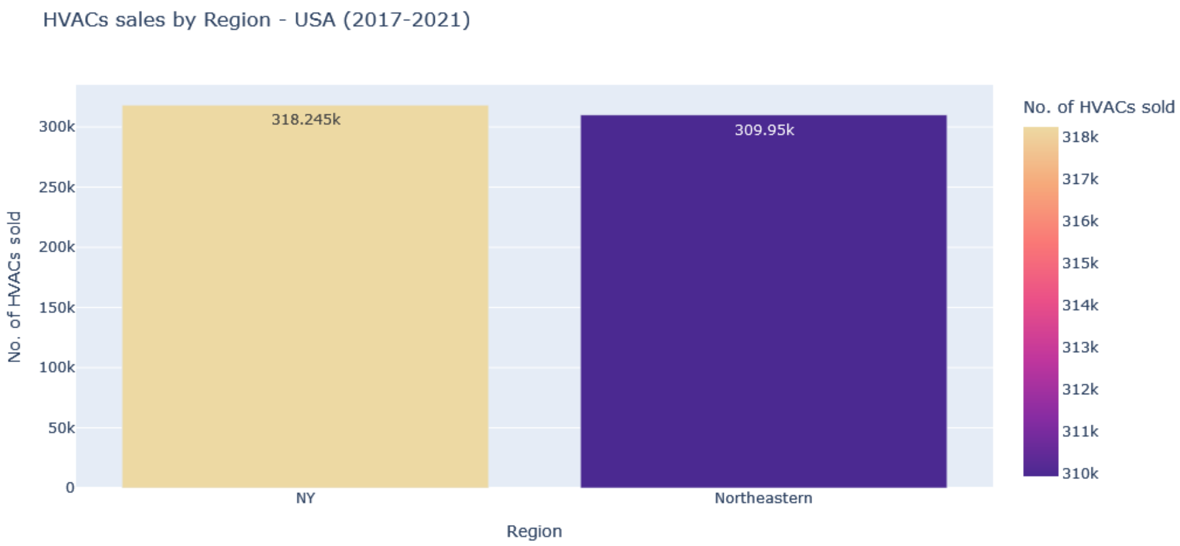


Fig 25. HVAC sales by region

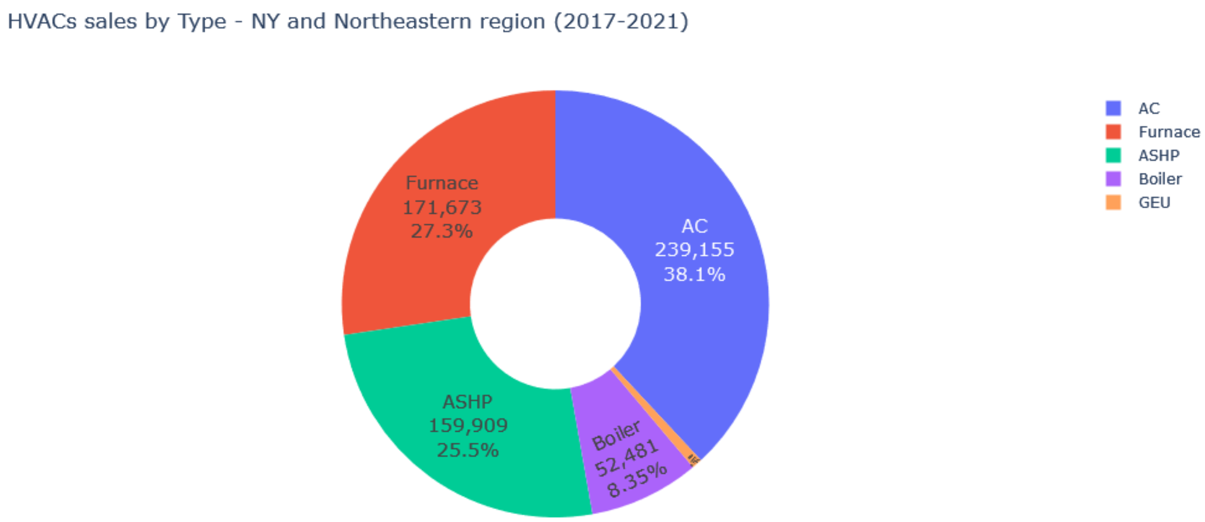


Fig 26. HVAC sales by type

AC – Air conditioner

ASHP – Air-source heat pumps

GEU – Geothermal Unit

Financial Equation

The Heating, Ventilation, and Air Conditioning (HVAC) sector in India is witnessing significant growth driven by various factors, such as rapid urbanization, increasing disposable income, and changing climatic conditions. Various government initiatives, like 'Make in India' – Atmanirbhar Bharat, Production Linked Incentive (PLI) schemes, financial incentives, and the commitment to become carbon neutral by 2070 are some of the prime contributors to an energy-efficient HVAC market growth.

Projected to reach a market size of $30 billion by 2030, and growing at a CAGR of 16.3% exponentially, the Indian subcontinent has become a fertile ground for local and international HVAC manufacturers. In India, the demand for HVAC systems has been steadily rising, propelled by the expansion of infrastructure, urbanization, and rising awareness regarding indoor air quality and energy efficiency.

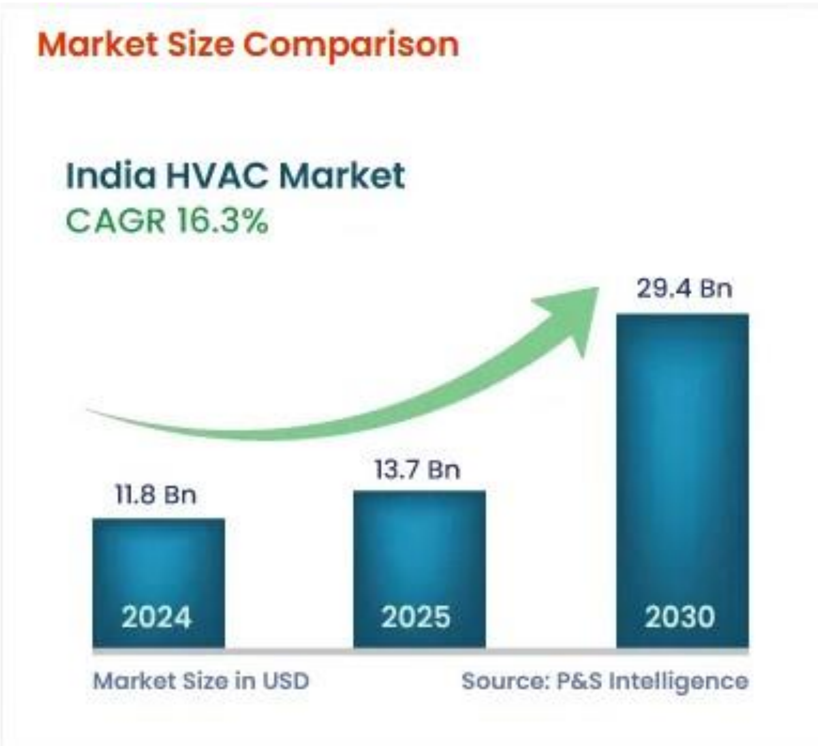


Fig 27. Indian HVAC market growth forecast

Exponential growth rate

Exponential growth is a pattern of data that shows greater increases with passing time, creating the curve of an exponential function. The formula for exponential growth is $V = S * (1 + R)^T$. The starting value is S, R is the interest rate, and T is the number of periods that have elapsed. The formula calculates V, which is the current value.

Exponential growth rate formula:

$$V = S * (1 + R)^T$$

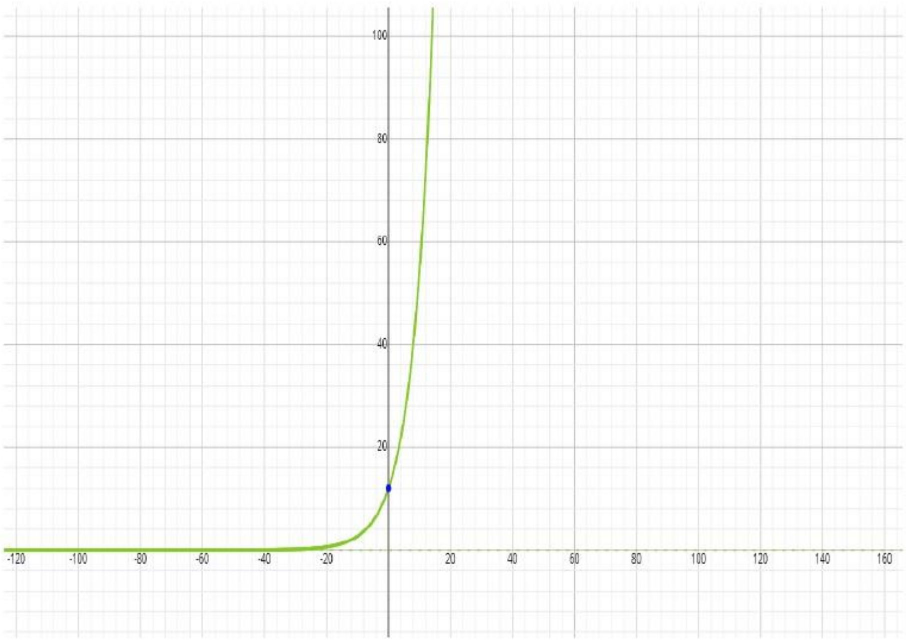
V = Current Value

S = Starting Value

R = Interest rate/rate of increase

T = Number of time periods

Since Indian HVAC market is growing at a rate of 16.3% (CAGR)



$$y = (1 + 0.163)^x \cdot 12$$

Fig 28. Exponential Growth Rate

Here, '12' is multiplied with the equation denoting $11.8 Bn (rounding off to 12) market size in 2024

15.0 Conclusion

HVAC systems account for more than 40% of building energy consumption, and are one of the main sources of carbon dioxide emissions. Machine learning methods could have a transformative impact on the optimization and control of HVAC systems, as well as on building design and fault diagnosis and detection. AI-integrated HVAC systems offer numerous benefits, including increased energy efficiency, improved indoor air quality, personalized comfort, predictive maintenance, and reduced carbon footprint.

16.0 References

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8. India HVAC sector – International Trade Administration. [link]

9. HVAC industry to grow at CAGR of 16%, says Daikin India MD. [link]