

Heating Control in Smart Buildings enabled with Reinforcement Learning



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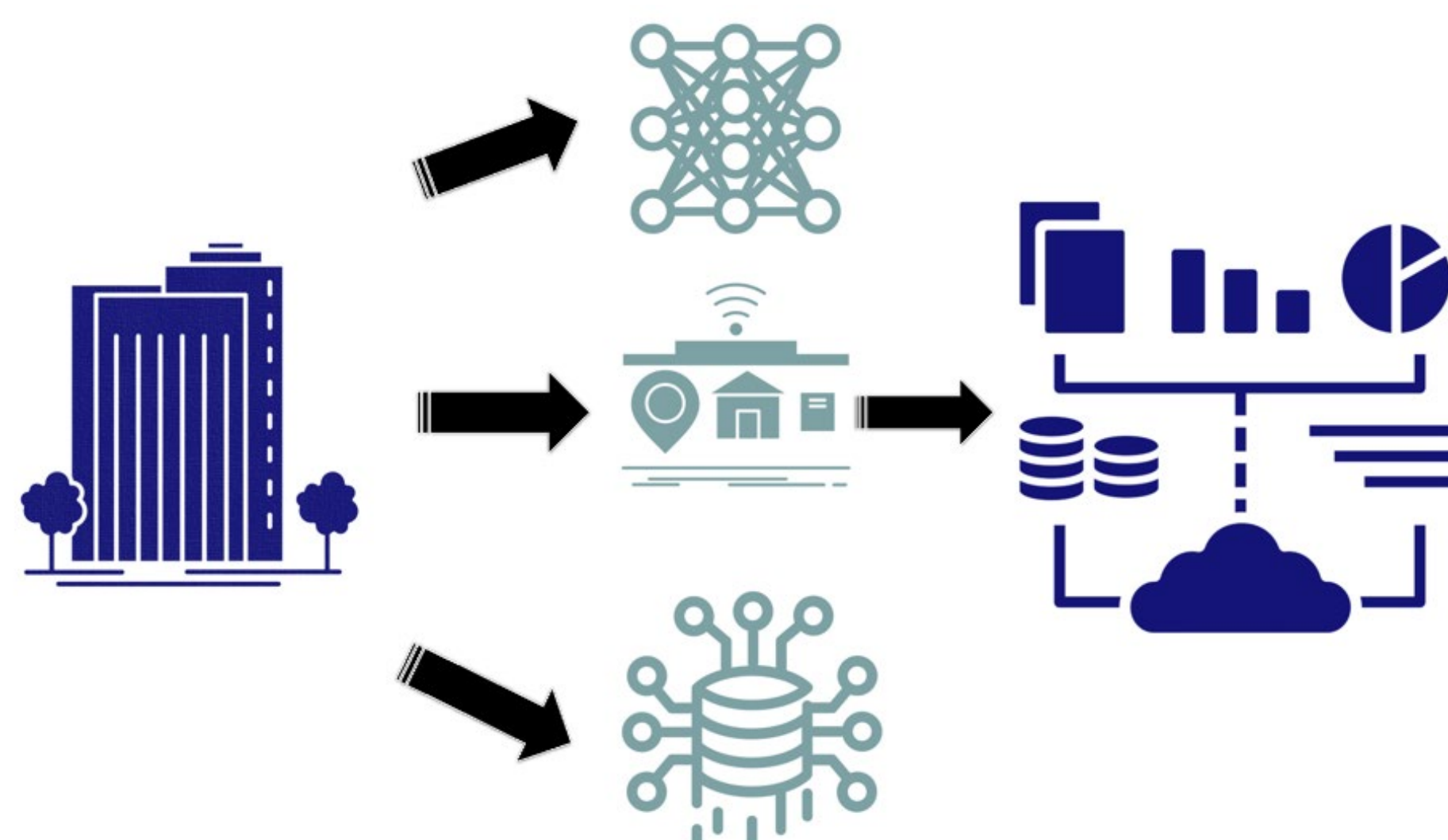
Introduction

Context

- Energy consumption in buildings reports having a notable portion of the total energy consumed globally. Heating and Air conditioner systems are accountable for 50% of building energy consumption in the US[1] and between 10 - 20% of overall use in developed countries.
- It is essential to design self-adaptable energy-efficient policies which adjust energy consumptions of heaters/air-conditioners in real time while maintaining comfort of occupants.

Emerging Technologies and Challenges

- Automation is the new future of the world, which is changing complete the lifestyle of people by integrating technology into their daily activities. Automating building operations and conversion of a building into a "Smart Building" is one of the significant sectors gaining interest in recent years[3].



- It is challenging to implement such a strategy due to multiple constraints and factors which contributes to unpredictable variations of the temperature inside buildings (external weather, occupancy, day/night, seasons, appliances etc.)
- Most of existing solutions rely on supervised learning techniques to build models, which require historical training datasets. However, these models often become obsolete when the environments changes (new features, new appliances, etc.)

Research Objectives

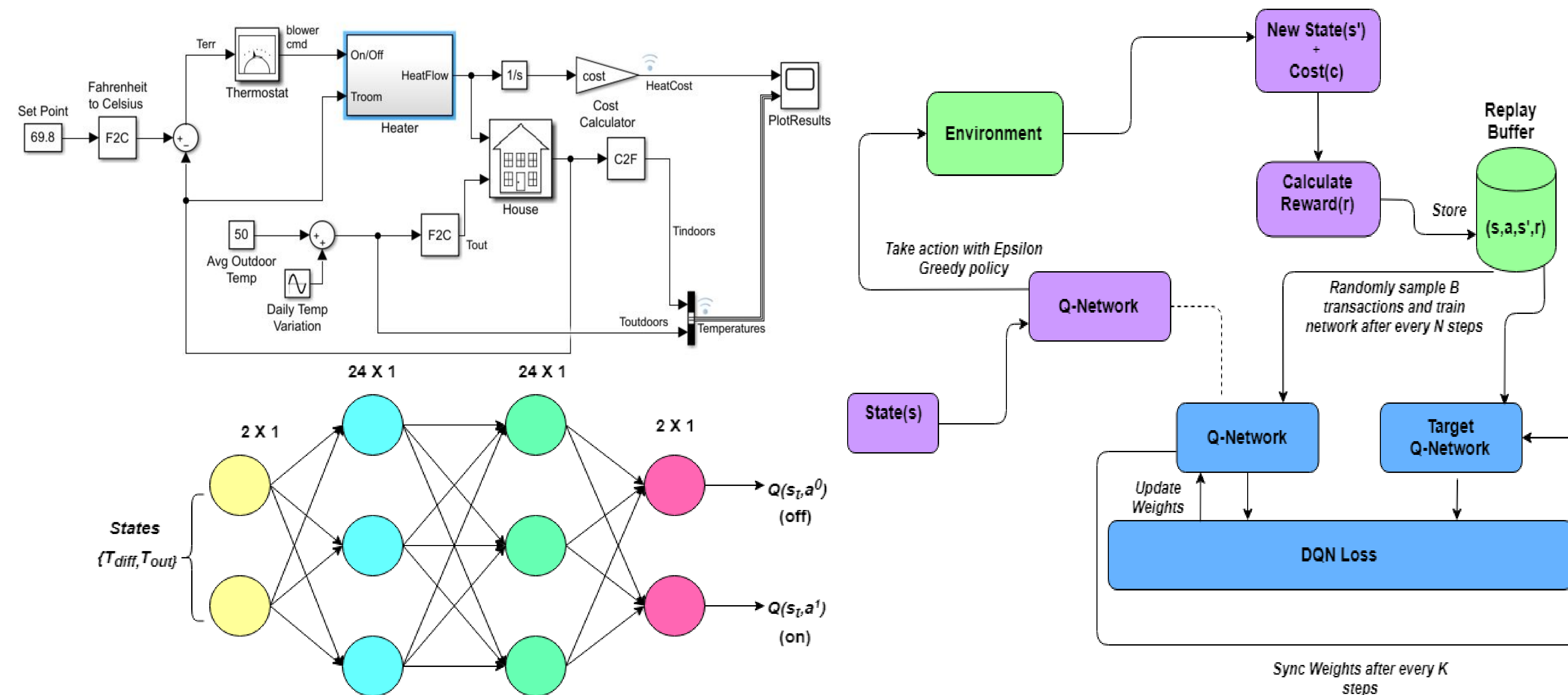
- The inappropriate settings of the set-points of heating systems, users may feel cold or hot despite more consumption of energy.



- This research aims to propose a reinforcement learning based methodology to build smart thermostats for heaters that allow controlling the temperature according to user preferences.

Research Methods

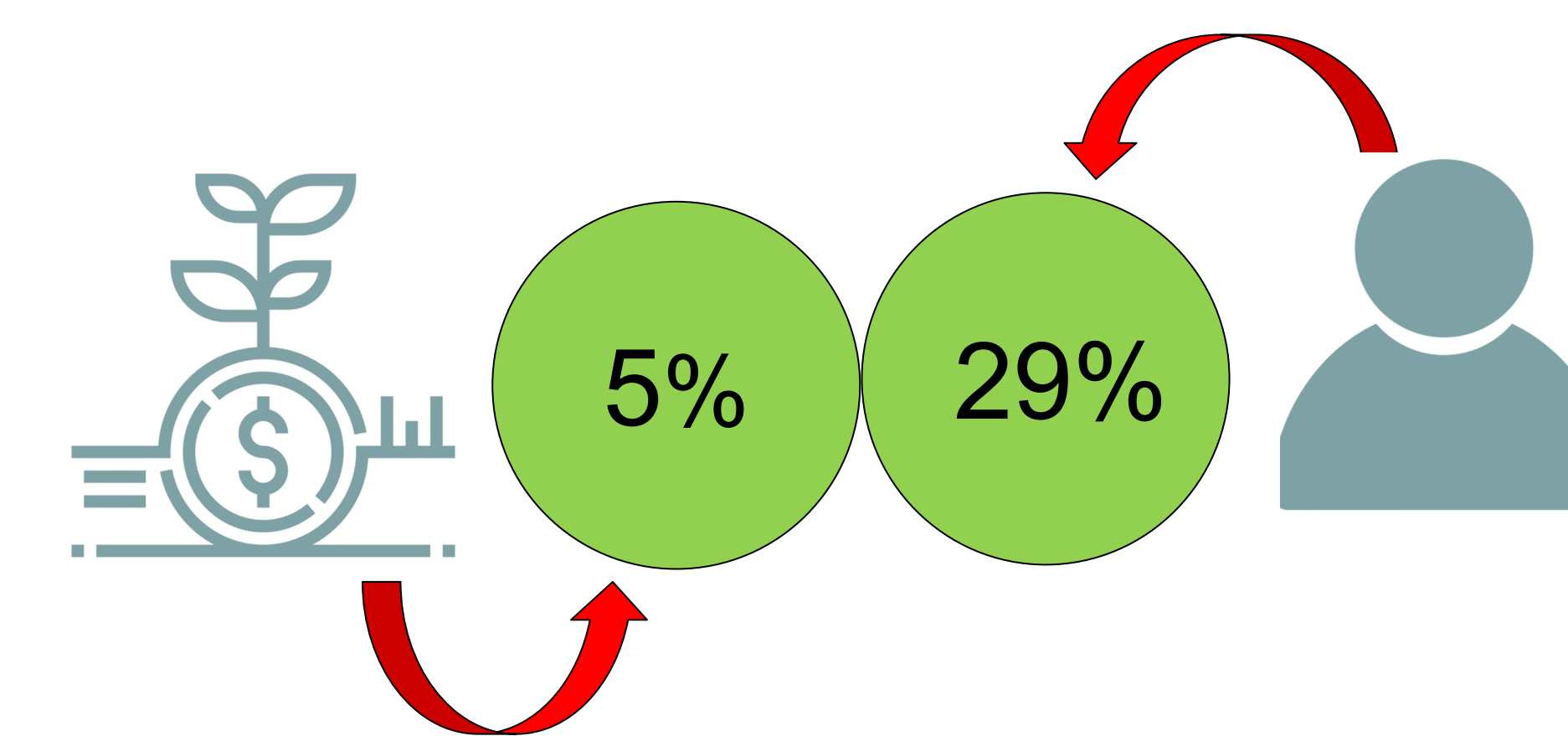
- Deep Neural Networks combined with RL are proving to get better results than tabular RL algorithms like Q-learning.
- A house heating system provided by MATLAB/Simulink is used as an environment and Deep Q-Networks(DQN) algorithm is implemented to train the agent.



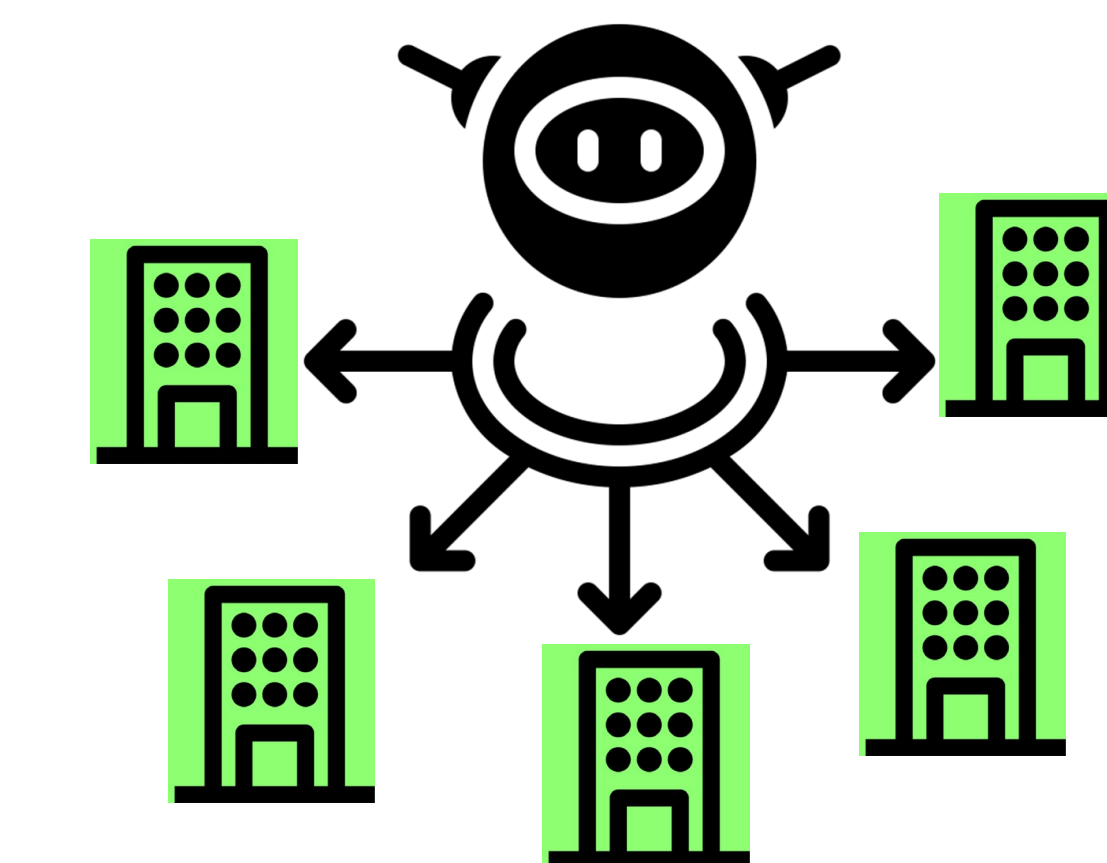
$$Reward = \beta(Cost) - (1-\beta)(Setpoint\ Temperature - Indoor\ Temperature)^2$$

Conclusions and Future Work

- This research presents a methodology to control the indoor temperature within a building by switching on/off the heater device to improve occupant's comfort while saving energy costs.
- The proposed model outperforms a rule-based thermostat which operates based on a threshold.



- Experiments are being performed to propose a central agent that can control a network of buildings incorporated into a smart grid.



Acknowledgement

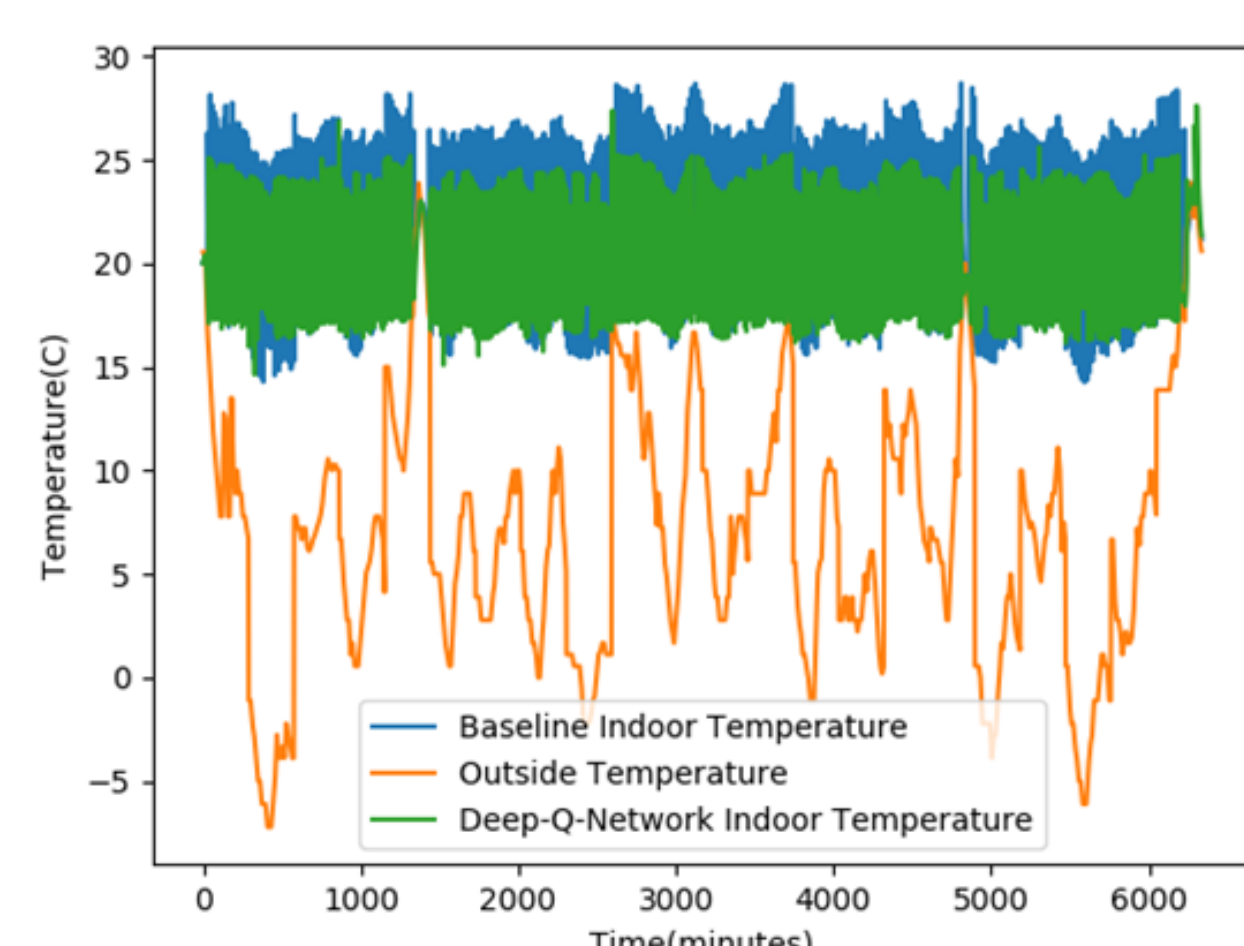
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References

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- <https://www.mathworks.com/help/simulink/slref/thermal-model-of-a-house.html>
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- <http://www.climate.psu.edu/>

Results

- Real world weather data of Philadelphia region for March 2019 is used as outside weather data to perform the experiments[4]. The model is trained on 22 random days from the month, validated on 6 days and tested on 3 days.
- The baseline model is dependent on a rule-based thermostat. The thermostat allows fluctuations of 2 degrees Celsius above or below the desired room temperature(21 degree Celsius). If air temperature drops below 19 degrees Celsius, the thermostat turns on the heater and if rises above 23 degree Celsius, the thermostat turns off the heater.
- Mean Absolute difference from the set point temperature(Mean) and heat flow is integrated over time and multiplied by the energy cost(Cost) is calculated to compare the performance of Baseline model with Deep Q-Networks model.



	Baseline Model		DQN Model	
	Mean	Cost	Mean	Cost
Train	2.42	437.42	1.75	421.42
Validate	2.51	146.95	1.79	138.36
Test	2.47	64.61	1.73	62.54

