Reinforcement Learning based Controller for Automotive HVAC Control

Daud Raza
National University of Science & Technology
draza.rime22smme@student.nust.edu.pk

Contents

Introduction

The energy consumption of Heating, Ventilation, and Air Conditioning (HVAC) systems in automotive applications is a critical consideration for both environmental sustainability and driver comfort. As vehicles become more technologically advanced and consumer expectations for comfort rise, optimizing HVAC control strategies becomes increasingly imperative. Traditional control schemes such as Model Predictive Control (MPC), Bang-bang control, fuzzy logic, and Proportional-Integral-Derivative (PID) controllers have been widely employed in automotive HVAC systems. However, these conventional approaches often struggle to strike an optimal balance between energy efficiency and occupant comfort.

Reinforcement Learning (RL) has emerged as a transformative approach in HVAC control, offering promising solutions to the challenges faced by traditional control methods. RL algorithms enable HVAC systems to learn optimal control policies through interaction with their environment, leveraging feedback mechanisms to continuously improve performance. By dynamically adjusting control actions based on real-time data and environmental conditions, RL-based HVAC systems can adapt to changing circumstances and optimize energy consumption while maintaining desired comfort levels for vehicle occupants.

- To be Continued -

Literature Review

Mckee2020: Deep Reinforcement learning for Residential HVAC Control with Consideration of Human Occupancy

The paper presents a DRL method to reduce energy costs in residential HVAC operation while maintaining comfort levels. The RL model being used in this scenario is a Deep Q Network, in which the values of the Q Table are estimated using neural networks. The neural network architecture and the algorithm for the RL model is mentioned in the paper, but many specifics regarding the base simulation model on which the controller is operating are not mentioned. Utilizing a multi-zone cooling unit, the DRL controller schedules HVAC on/off commands based on dynamic energy prices. It employs precooling strategies during low-price periods to cut costs without compromising comfort. In simulations, the DRL controller achieved a 43.89% cost reduction compared to traditional fixed-setpoint operations, indicating potential for real-world application in smart homes for energy-efficient automation. The system is prepared for live, real-time testing in residential environments, aiming to validate the simulated savings and operational efficiency in actual use cases. Overall the paper is short and concise, and provides some details regarding how the reward function was structured.

Yang2021: Towards healthy and cost-effective indoor environment management in smart homes: A deep reinforcement learning approach

The paper presents a study on autonomous indoor environment management for smart homes using a deep reinforcement learning (DRL) approach. The methodology involves formulating the problem as a Markov decision process and employing a double deep Q network (DDQN) with prioritized experience replay (PER) mechanism. This strategy enables adaptive control decisions without requiring forecast information of system uncertainties. The results demonstrate the method's adaptability to variations in weather conditions, electricity prices, and home occupancy patterns. It also shows a reduction in average daily energy cost by 3.51% and 8.56% in winter scenarios and 4.05%, 7.88% in summer scenarios, while maintaining indoor air quality and temperature within desired ranges. The approach offers a promising solution for optimizing indoor environmental quality and minimizing energy costs in smart homes. There are some issues with the paper in regards to validation. The model for the house environment has not been compared in the paper with any baseline benchmarks, so there is some doubt whether the model actually operates in accordance to actual physics. Secondly, the method for comparison between the MPC, DDQN, and DDQN-PER is explained in detail.