Intelligent HVAC Control System

by

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Dedication

This thesis is dedicated to a study within the automotive industry. It is to promote and encourage the use of intelligent systems and contribution to the growth in the Autonomous space of transportation.

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Abstract

Comfortability where occupant is presence is the subject of marketing in many sectors. While there are many areas that contribute to comfortability, this research paper focuses on Heating, Ventilation and Air Conditioning (HVAC) in the transportation sector. A literature survey has been conducted to understand historic HVAC control and optimization approaches. State of the art shows many control approaches captured/compared and provide great potential but also agree that there is still room for improvement. In addition, other reviews were also compared to examine their studies in this area. Some of the earlier approaches use standard control features but as time progress and more tools and technology become available, the HVAC control development progressed even further to integrate artificial intelligence and machine learning and open new opportunities for improvement/optimization. This research explores a unique control opportunity using Linear Discriminant Analysis (LDA) to predict the occupant and then follows it with Kalman Decomposition (KD) for real time controllability/ Observability post LDA operation. Integrating these two tools provide results as new combined approach for HVAC control. Prediction algorithm LDA shows approximately 79% accuracy score for prediction which scores above average when compared to other algorithms and sensors used. KD is manipulated to be controllable and observable to maintain cabin temperature in real-time once the occupant is identified. Future work for additional development/improvement are also mentioned in the conclusion in future work section.

Chapter 1 : Introduction and Historical Background

1.1 Introduction

Comfortability comes in many ways. It can be the comfort of a seat, comfort of wearing an apparel, comfort of sound or even comfort of water temperature in a pool but all have one thing in common, consumer satisfaction. This study is elaborated by looking at comfort in the air that keeps the environment warm during colder seasons or cool during hotter seasons in a closed space environment such as buildings and most importantly to this review, transportation vehicle.

The transportation sector has been evolving rapidly, namely the automotive industry. The automotive industry has shown exponential growth and advancement in technology such as the Energy consumption, Safety measurements, Electric drive motor performance, Autonomous technology and many more. Many countries from around the globe have contributed to this innovative growth as government regulations are put in place to help promote clean energy and reduce CO2 emissions [1]. The ability to implement artificial intelligence has extended opportunities for innovative development in the area of automation to be able to provide a more hands free state-of-the-art travel experience.

In today's fast-moving paste, culture change continues to grow because of technology advancement usability and adaptation and therefore consumer demand has also increased significantly as competitors work to accommodate it. Consumer demand is often viewed as the product of customer satisfaction and cost in the space of the automotive industry. The importance of customer satisfaction is often the number one priority within any company. There are many variables that provide customer satisfaction such as affordability, environmental comfortability, product longevity, and a number of other features. This study will tackle on one of the key areas in environmental comfortability known as Heating Ventilation and air Conditioning (HVAC), A system used to control thermal condition in vehicle cabin. A proposal is put forward to develop an HVAC that enables the user (i.e., the consumer) to have a more advanced interaction that can result in a more efficient user interface and user input requirement. This literature survey reviews the advanced technology in the area of machine learning that have been discovered and/or implemented to automate the HVAC control system. The purpose of this literature is to identify past, present, and future advances/intelligence that automate HVAC controllability and the comfort for consumers as they provide their feedback based on their continuous alteration of temperature setting for their comfort. It looks to identify any room for improvement of further advancement.

The survey below details some of the technology that has been discovered in previous studies by academia, conferences, companies, and other sectors that have conducted and published their work relating to this area and will also provide a guide to what kind of optimization can still be improved/implement within the scope of studies that have been reviewed. The review will also survey areas outside of the automotive industry that relating to intelligent HVAC control.

1.2 Classification of Past, Present and Future

Technology growth has increased rapidly in recent years due to demand, use and availability of new technology [2]. As more discoveries of new technology are introduced, better support is provided for other innovative technologies to be discovered and become available for use. The competitiveness of companies and labs have also driven these innovative discoveries as the never-ending race continues to progress and grow as new players enter the field from nearly every direction. As better technology becomes available overtime, HVAC can also be a vulnerable apparatus for its openness and broadness of implementation for new ways to serve and provide living comfort. This has proven to be true as the historical functionality and control of HVAC has also evolved because of new technology. classification of past, present and future based on discoveries shown in table 1 summarizes and classifies historical algorithm found in previous studies captured within this scope to date.

1.2.1 Past Work

In the Past, HVAC has used a standard controller process of simply turning on the HVAC unit when feeling discomfort and keeping it on and then turning it off when feeling discomfort on the other extreme [3]. The controllability then evolved a bit further to provide more freedom to the consumer by maintaining to the set temperature without the need for manual process of consumer interaction such as the standard ON/OFF to turning it on and off for comfort. This was achievable with the aid of Proportional-Integral-Derivative (PID) driven controller. The PID control strategy has been around for more than 80 years when it was first brought forth in 1939 [4] The use of PID also practices a similar strategy of controlling HVAC to either provide hot air or cold air flow throw the ventilation with proper humidity to reflect occupant preferred setting. In the winter it would turn on to provide hot air with variable flow and turn off when closed space reaches or began to exceed set temperature. Whereas in the summer it would turn on to provide cooler air with variable flow and turn off when closed space reached or began to exceed set temperature. PID can also be used for different types of heating methods such as the hot water heater system [5]. There have been further developments to PID over the years to enhance its usability such as integrating it with Fuzzy logic approach [6]. In addition to PID there are other breakthrough technology that had significant impact on controllability and communication in this present time.

1.2.2 Present Work

In these present times wireless technology has been emerging and usability has been growing rapidly especially with the help of big data [7]. In addition, wireless technology via internet has enabled unlimited opportunities for growth of wireless devices as time goes on. The internet has been one of the most critical resources for communication and operation of daily activities on a global scale [8]. The internet is the main contributor for a breakthrough technology called Internet of Thing (IoT) that has significantly impacted the growth of making the internet one of the most reliable resources. While there are other wireless technologies such as Bluetooth, RFID, and other short/long range method, the IoT is found to be most versatile. IoT was discovered in 2000 and first official publication became available to the public in 2002 [9]. IoT can be classified as an expanded network communication that enables communication between two apparatuses over the internet. These apparatuses can be devices such as wireless phones, doorbells, tablets, scanning devices, thermostats, etc. or they can be device built in machines such as autonomous vehicles, airplanes, testing machines, and anything that can receive and/or send data over the internet. In the scope of this survey, the focus will be on smart thermostat. The “Smart” thermostat control technology capability might be considered one of the most breakthrough technologies for HVAC in this present time. The use of Smart thermostats have increased significantly as they have become noticeable for enabling opportunity for saving energy [10], [11], [12], [13]. The ability for an HVAC controller to be linked to other devices via internet communication provides a wide variety of opportunities for control stability, data mining and proactive technology management. This is one of the reasons the automotive industry has been outstandingly widening the enlargement of IoT compared to other industries. In the past, analysts forecasted the technology will be implemented in nearly quarter of billion vehicles by year 2020 [14], [15], [16], [17], [18]. One of the key challenges for IoT that may be a topic to try to resolve is security due to the amount of personal and confidential data that can be exposed [19]. There is always room for developing a more robust wireless communication protection system that prevents it from being vulnerable to hackers. This may be a good topic for future studies.

1.2.3 Future Work

Future HVAC control resources may not be as challenging as it was in the past due to the number of finding and variety of approaches that have been discover. While resources are widely available, there are still challenges to increase efficiency because HVAC is considered to be an apparatus that has high energy consumption [20]. Previous Studies have shown that energy efficiency will vary depending on where is the location that is being examined and how it is affected by climate change compared to others using the same control strategy [21]. Control strategies can still be complicated as Tacklim Lee et al. proposes for future work control strategies to take advantage of bigdata analysis. The future forecasts that breakthrough development of control will most likely involve software algorithms as more control approaches have been steering towards Artificial intelligence and Machine learning. Jianxin Wang et al. also mentioned the challenges researchers may be facing as they shift to these types of control systems will most likely be security concerns as they implement the use of IoT/wireless technology. Studies to mitigate the internet security complexity may not be easy as vendors work effortlessly to earn their consumer's trust. As this study focuses on the scope of transportation, Namely the automotive industry, it is important to note that vehicle manufacturers will also have the same security concern. Abdur et al. also expressed the concern of security in vehicles as more functions within the vehicle may rely heavily on IoT.

A lot of the research that has been conducted within the scope of HVAC in automotive are mainly targeting occupant comfort and energy consumption efficiency. As the automotive industry progresses into battery electric vehicles (BEV) and autonomy, energy consumption will be the focus for providing longer mile range per charge. Future breakthrough would have to include shorter charge time and increase of charging stations [22], [23], [24] if HVAC energy consumption is not reduced significantly. This was not a huge concern with conventional internal combustion engines because the heat radiated from the IC engine would often be used to support the HVAC system [25]. There is a dilemma with full electric vehicles that would need to be addressed via optimization or increase energy storage banks in a vehicle to meet energy losses. Electric vehicles show a 33% of their energy being consumed by heaters and air conditions [26] while HVAC in buildings Account for nearly 40-50 % of energy consumption [27], [28], [29], therefore there is no doubt that energy consumed by HVAC system is significant and require attention. In addition, depending on outside ambient air temperature, HVAC energy consumption can reduce driving range on electric vehicle up to 50% [30], [31] and 60% on extremely cold temperatures [32], [33]. As the electric vehicles become more popular and more automotive companies are committing to full electric transportation in the future [34], [35], [36], it is critical to consider ways to reducing energy consumption while still meeting consumer demand and comfortability. The next breakthrough for the future of HVAC should either be the findings of an efficient HVAC system or the findings of a higher energy storage bank utilizing acceptable real estate area in a vehicle. Normally BEVs are capable of being equipped with battery range of approximately 20-80 kWh [37].

	PAST	PRESENT	FUTURE
Discoveries	Before discovery of IoT	During discovery of big data	Optimization of energy Consumption and storage
Types of Control Algorithms	GA Fuzzy PMV PID PMV	GA DMC GPC Fuzzy MPC PPD PH/LH ON/OFF PMV ANN PSO PID	GA Fuzzy PH/LH PSO PID AI
Time	t<2000	2000<t<2020	2021<t

Table 1: Historical highlights of HVAC control strategies

1.3 Purpose of HVAC and How it Works

Heating Ventilation and Air Conditioning (HVAC) has been around for decades to provide comfortable temperature environments in closed space in several areas such as residential, industrial, space and transportation (i.e., automotive industry). The Refrigeration process was introduced prior to 1900s and was later expanded and showcased in the early 1900s [38]. It continued to develop and was expanded to be utilized to control temperature in closed space in different types of environments as shown in figure 1. This survey will mainly focus on the improvement of utilization of HVAC in the automotive industry, namely in the cabin space but will also explore approaches used in other areas in an effort to evaluate other opportunities of control theories/approaches.

History of HVAC has shown great progression and momentum for innovative development as indicated by ASHRAE [39]. Table 2 below summarizes information from ASHRAE site. It shows the history of HVAC as it expands in multiple areas of living areas for humans, animals, and others. Notice that by 1969 more than half the vehicles produce come equipped with AC at minimum. While ASHRAE did not provide historical data beyond 2015 in

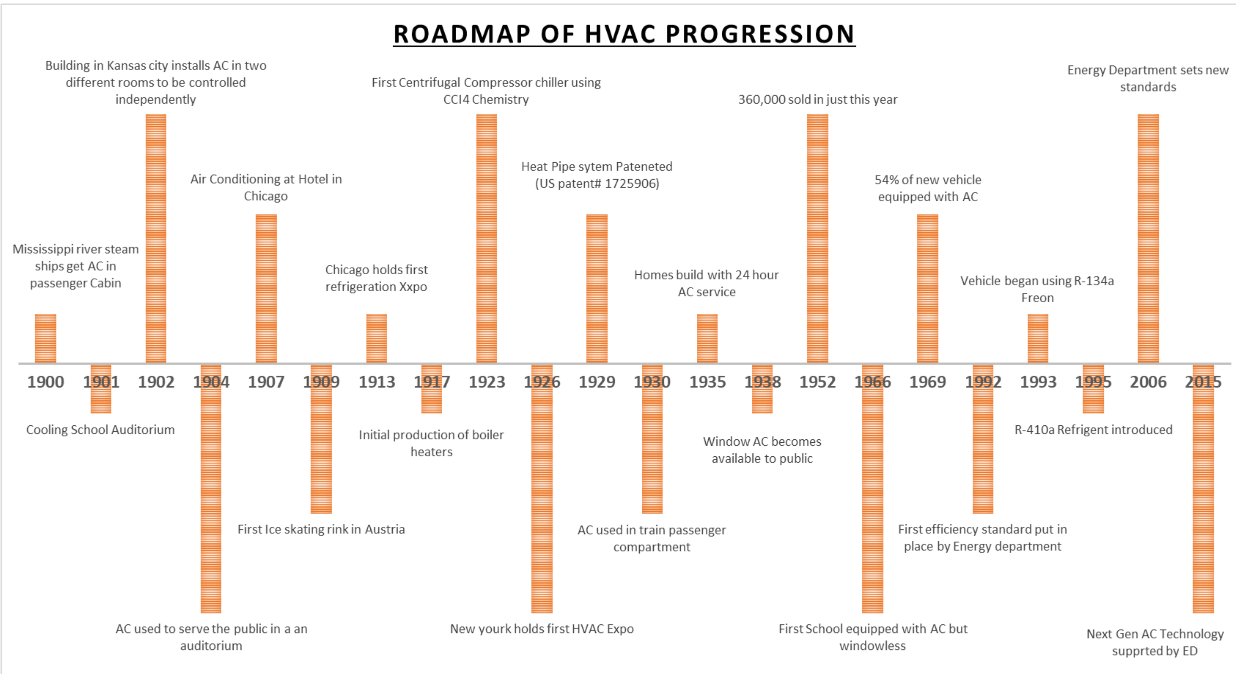

Figure 1: Roadmap of HVAC Progression provided by (ASHRAE)

this aspect, there are other discoveries and optimization after 2015 for HVAC that will be mentioned more in this review and is a clear indication that there is potential for HVAC usability to grow even further.

The HVAC system has been used in the automotive industry since 1939 when the air conditioning was first introduced on a vehicle line called the Packard [40]. It was far more manual to operate than the technology that exists today, but it worked as intended which is to provide passenger comfort temperature in the cabin relative to outside ambient air temperature that often steps beyond comfort boundaries. Temperature control in vehicle cabin started as a luxury feature but would later transition into a necessity due to the adaptation, increasing capabilities and function of transportation vehicle and the need for these features.

Date (Year)	HVAC Progression (ASHRAE)
1900	Mississippi river steam ships get AC in passenger Cabin
1901	Cooling School Auditorium
1902	Building in Kansas city installs AC in two different rooms to be controlled independently
1904	AC used to serve the public in a an auditorium
1907	Air Conditioning at Hotel in Chicago
1909	First Ice skating rink in Austria
1913	Chicago holds first refrigeration Xxpo
1917	Initial production of boiler heaters
1923	First Centrifugal Compressor chiller using CCl4 Chemistry
1926	New yourk holds first HVAC Expo
1929	Heat Pipe sytem Pateneted (US patent# 1725906)
1930	AC used in train passenger compartment
1935	Homes build with 24 hour AC service
1938	Window AC becomes available to public
1952	360,000 sold in just this year
1966	First School equipped with AC but windowless
1969	54% of new vehicle equipped with AC
1992	First efficiency standard put in place by Energy department
1993	Vehicle began using R-134a Freon
1995	R-410a Refrigent introduced
2006	Energy Department sets new standards
2015	Next Gen AC Technology supprted by ED

Table 2: Summarized table of HVAC historical timeline (ASHRAE) as of 2015 only, more recent findings may be added.

As the evolution of HVAC may appear to reach a plateau, it is still interesting to evaluate the improvements and innovative approaches conducted in the field of HVAC control. The HVAC system is not that complicated when viewed from a high level. Aside from the controller portion of it, it simply takes in ambient air and modify the temperature and humidity levels by flowing through evaporators, heater core coil for increasing temperature or flowing through cooling coils filled with refrigerant to reduce temperature. Many studies have been conducted in field of HVAC in attempt to provide more comfort while maintaining energy efficiency [41], [42], [43]. Studies will be discussed further later in this review. There are other apparatuses that are involved in the system such as compressor, Condenser, fan, valves, etc. that work to better maintain living environment due to natural factors such as humidity, debris, etc.

The Controlling portion of HVAC can be very simple or very complex depending on the tolerance bands allowed for set temperature. Control techniques and factors will be evaluated deeply throughout the rest of the paper but in essence it can be said that HVAC control varies in approaches but similar in location settings.

1.4 Driver/Passenger Identification Strategy

This section of the review will examine the variety of strategies that have been discovered to identify passengers in vehicle. In the last nearly four decades, human identification has enhanced due to new innovative discoveries. As technology continue to advance in its nature, it opens more opportunities for improvements in the space of human identification. Today, with the support of advanced technology resources, human identification has been expanded to enable a variety of approaches such digital fingerprint, facial recognition, eye recognition, passcode verification and other identification approaches. The scope of this review will only encompass the biometrics such as fingerprint, facial recognition, and passcode verification. Others will be discussed but will not be evaluated as a candid approach. Table 3 captures some of the highlights for studies related to identification verification. It can be seen that each approach has its own positives and negatives.

The automotive industry continues to advance in all areas. Vehicle engineers have introduced many ways to assign vehicle to drivers some of which include biometrics. Although some were not successful due to outdoor environment variables such as weather and debris, there are other technologies that prove to be robust as shown below.

Identification Verification						
I.D. Type	**Required Equipment**	**Settings**	**Secure Level**	**Advantages**	**Disadvantages**	**Reference**
Driving Behavior	Assessment Algorithm Unit	Vehicle	1 (Min)	Easy to implement. All Variables already exist	Required some driving distance before it can be activated	[44]
Finger Vein	Infra-red CCD Camera	Vehicle, Non-Vehicle	3 (Max)	easy to Implement. Does not require to make contact.	Does not work for driver with finger disability	[45]
Occupant Count	Occupant Mobile Device	Vehicle, Non-Vehicle	2	Easy to implement	Required everyone to have a mobile phone	[46]
Body Temperature	RGB Video Image	Vehicle, Non-Vehicle	2	Easy to implement	May classify animals as human	[47]
Facial Recognition	HD Camera	vehicle	3	Easy to Implement, High Accuracy	Cannot wear facial covering such as Mask, Sunglasses, etc.	[49]
Finger Print	Sensor	vehicle	3	Easy to Implement, High Accuracy	Cannot wear gloves	[50]
RFID Card/Tag	Reader	Vehicle	2	Easy to implement	May be used by others	[60]
Entering Passcode	Keypad	vehicle	2	Easy to implement	Inconvenient	[61]
Iris Recognition	HD Camera	vehicle	3	easy to Implement. Does not require to make contact.	Cannot wear sunglasses	[62]

Table 3: Driver Identification strategy

Studies have shown approaches that show some potential such as one that identifies the driver based on their driving behavior [44]. It monitors the behavior of the driver using the acceleration and brake pedal. In addition, it considers the vehicle speed and distance the driver keeps between their vehicle and the vehicle ahead. It determines the driver's identification based on these parameters. This is an interesting approach to identify the driver but will not be able to serve the purpose of driver identification input for the intended project because this key variable is required as soon as the driver enters the vehicle. The intention is to identify the driver as soon as they enter the vehicle or when they are approaching the vehicle and set the cabin temperature to the driver's preferred settings.

While drivers cannot afford to drive for some distance before their identification is recognized by the HVAC control system, there are other approaches that can prevent that delay.

The survey came across an approach that identifies the driver based on their finger-vein with Radon transform and image processing using neural networks [45]. The biometric approach utilizes an infra-red CCD camera to capture an image and perform processing to identify the finger-vein traces. The study shows it to be successful and has more potential than other approaches due its ease of implementation. It does not required individuals to make contact with the sensor and is classified to be very secure allowing it to expand its usability and longevity. While the study shows good potential, one variable that was not mentioned is if this approach is still functional while wearing gloves. It is probably worth exploring and discussing potential outcome for consumers wearing gloves or other type of material that may be covering the finger.

An example of utilizing other smart devices alongside HVAC that was found to be interesting is the novel activity and occupancy estimation methods for intelligent HVAC system [46]. This approach focuses on determining the number of occupants in the space required to be controlled by the HVAC. It uses the sensor technology on smartphones to significantly achieve higher accuracy of presence of occupancy compared to other approaches. Overall, it basically implements the microphones and accelerometers found in smart phones to understand the discomfort of the occupant and control the HVAC based on that. It does indicate that the system works well when phones are present nearby the users and not left in another room. While this approach provides comfort based on occupancy presence and their movements, it cannot be used in vehicle cabin settings because occupants are normally sitting down with their seatbelt strapped which prevents them from expressing their comfort based on their movement. In addition, many users are not comfortable with enabling their personal devices to be a listening ear, although many have adapted to other portable devices in their homes such Amazon's famous "Alexa" or other devices in that category.

While there are several approaches that utilize facial recognition to identify presence of human being, an interesting approach that this review came across monitors the temperature of human body via RGB video image [47]. It measures thermoregulation state of a person to indicate their thermal comfort. In addition to the concept, it utilizes the Eulerian video magnification approach to help manipulate the image to extract the necessary information for thermal comfort determination. This approach is good and potentially cost effective since it does not require special equipment or other integration of expensive systems. This study was conducted for an office area and could potentially be replicated in a vehicle cabin environment. This approach could be advanced further to learn and keep record of users to be able to potentially automate the whole system. This could also work with vehicle security technology that utilizes driver identification to determine when to enable and disable systems in a vehicle. Such an approach has been patented by General Motors for vehicle security [48]. It prevents the vehicle and other system in the vehicle from enabling if it does not recognize the user. In addition, once it recognizes the user, it can automatically set memory, etc. to the user preference. The study does not specifically indicate any control of HVAC to driver preference, but it can be a good feature to include. There were several discussions regarding how the vehicle identifies the driver. There are several options available that were evaluated and rated based on cost, mainly, and other variable such as methods of correctly identifying the intended driver.

A comprehensive approach using facial recognition alongside other sensing instruments for detecting presence of a living being in the vehicle was also patented to address safety concern for extreme fatal temperatures [49]. This is a good approach for the safety of a living being because it can also detect when coming near hazardous temperature in the cabin and take corrective action as a response to balance the environment within. The finding suggests using several ways to address the hazardous temperatures in the cabin including the control of HVAC. It suggests that the system response could have control of the engine to be able to start the engine to allow for air cooling when temperature is too high or allow for heating when temperature is too cold. This is all great because it aims to deliver safety and comfort of living being in cabin. If this system is implemented in a vehicle, it means that it would have all the required apparatuses to learn the driver/ passenger's preference. It may even be viewed as having too many apparatuses, but that cannot be argued when it comes to safety. The system then can be developed further to maintain a temperature based on the driver/ passenger's preference whenever possible without the need of a person controlling at the start of every trip.

An easy-to-use driver identification system that was evaluated consists of fingerprint technology in an effort to maximize security for driver identification in real time [50]. It relies heavily on machine learning, namely Convolution neural networks (CNN) to achieve quality real time driver identification. The algorithm provides continues updates as it continues to loop. This study is more representative because it is performed in real world application with data banked for a non-simulated vehicle. A number of other studies have been conducted in the area of vehicle driver fingerprint identification to provide a more secure approach [51], [52], [53], [54] and have shown great potential.

A lot of studies have been conducted to utilize RFID in a vehicle for multiple purposes. Studies show that RFID have been used to track moving object some of which are vehicles for purposes such as vehicle identification and tracking especially in areas of large number of fleets [55], [56], [57], [58], [59]. An interesting study show RFID to be utilized to identify vehicle details such as insurance, registration, annual inspection, etc. to help protect the loss of these required documents and the inconvenience presence of type of format for all these documents

[60]. This approach provides opportunities such as keeping exposed documents privacy protected and keep electronic records and accessibility. This information would be retrievable using an RFID tag, which could similarly be the same for driver identification. Access to this information can only be acquired by individuals that have access capabilities. The admin can manipulate access levels for each account.

Other ways for driver identification that may be simple and secure is an approach used by almost all security entry required data banks which is simply using a password or passcode. Aside from other technology implemented such as SMS alert, this approach [61] has been used to protect theft of a two-wheeler by requiring password to activate the ignition system. The same approach can be used to identify different drivers to manipulate the vehicle settings to their preference. This may not be the most convenient approach in case the driver forgets their password but it’s one of the most secure approaches.

A highly secure identification approach that can be used and maybe a bit more expensive too is the use of Iris Recognition to identify the driver such as the one studied for the use on an ATM [62]. While security is not a concern for the HVAC application but the robustness of individual identification in this technology can be used to identify drivers and operate the HVAC system to their set preference.

1.4.1 Security of Wireless HVAC Control

This section touches on the latest technology studied for securing HVAC controls when operated using wireless technology. The hacking of wireless technology is not new, and protection must be implemented especially when risk factors include severe damage that can lead to fatality. Vehicles in general must be protected from any hijacking because they can be life threatening when in the wrong hands.

A study conducted on smart building security in the UK identifies key factors that are at risk of harmful intrusion due to the fragility of their protection [63]. While it only addresses smart building only, it does provide a comprehensive review of systems subject to harmful wireless hacks [64], [65], [66], [67], [68], [69], [70], [71]. The hackers attempt to disturb wireless devices in any way they can when entering a network that is vulnerable. Often, when the network becomes larger, it makes it difficult to secure such in the case of J. Wan et al. when studying a smart factory [72]. They introduced a solution that integrates blockchain to help provide more protection to the network. Their proposal showed to have enhanced the network security and will be further studied in the future. Blockchain has also been studied in vehicles to help aid securing automotive networks from intrusion due to the emerging increase in wireless technology being integrated in transportation vehicles [73]. There is potential for this technology to provide protection in the automotive industry as it continues to grow and enhance.

Overall, Since the introduction of internet based wireless technology to the automotive industry, privacy and security has been a key topic. Many studies have come forward in an effort to preserve security and privacy for users with vehicle that have wireless technology integrated. Security protections continue to develop and enhance as hackers find other avenues to manipulate the system. There are many studies out there that detail different approach for different circumstances especially with the development of autonomous vehicles.

1.4.2 Driver/ Passenger Temperature Input

Transportation cabin occupants tend to rely heavily on temperature control strategies during extreme weather temperatures as they travel for long distances. The level of comfort on a journey inside a transportation vehicle is significantly impacted by how well the temperature can meet the passenger’s demand. In addition, comfort can be disturbed if traveling in battery electric vehicle and is consuming a lot of energy due to HVAC operating too frequently. While the occupant is looking for comfort, they may use various ways to input the temperature settings. One of the most common approaches are simply to manually input settings at the controller user interface. Figure 2 shows a high level of control architecture of what HVAC would require for operation. It is often similar to other control theories for different applications.

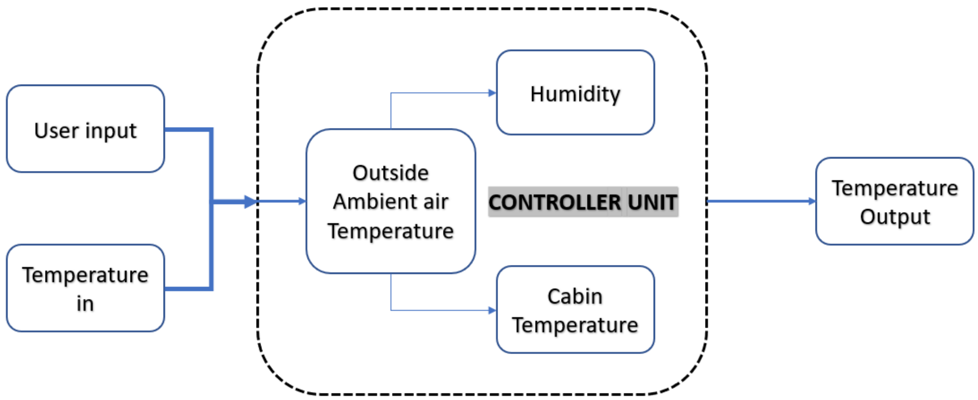

Figure 2: High Level HVAC Control Architecture

Other approaches for inputting temperature settings can be determined based on the delta of outside ambient air temperature, indoor air temperature or other factors such as outside wind, time of day and humidity that may contribute to change in temperature. All these can be variables that contribute to temperature settings and controllability.

1.5 Cabin Temperature Control

In this section, methods of control strategy will be evaluated to understand how well HVAC control has been optimized. Table 4 in this section summarized the findings and captured key features as well as advantages and disadvantages of the algorithms reviewed in this study. It can be seen how the different algorithms and control methods are used for HVAC control systems.

An intelligent method/algorithm for thermal control and optimization for energy savings was assessed to explore the effects of the proposed approach [74]. It utilizes Fuzzy control algorithms and predictive control algorithms Such as DMC and GPC to tune the control of the thermal source. This study was conducted in a building environment using Predicted Mean Vote (PMV) which relies on several parameters such as ambient temperature, humidity, air velocity and mean radiant temperature. The hierarchical structure approach was split into four layers called direct control, supervisory control, optimization, and planning layers. The direct control layer is responsible for providing access to controller and utilizes fuzzy logic along with PID algorithms. The supervisory control layer used for prediction integration, which relies on the output from the direct control layer for calculations. The optimization layer is then utilized to calculate for most comfort environment. The final layer called planning layer is then used to define an area in the controller that is the most energy efficient but also maintains a higher standard of comfortable climate environment. The study utilizes Simulink to model building HVAC environment to simulate the proposed approach to achieve maximum optimization. It compares result between DMC and GPC algorithm. Comparing the output with the reference, it shows results within expected boundaries. This study did not consider implementation in a vehicle and therefore did not factor parameters due to vehicle transportation and other variables that may contribute from/during high speed.

		Uniqueness		Past (t<2000)	Present (2000<t<2019)	Future & Proposed Future (2019<t)	Feedback		Space			
Classification		Advantage	Dis-advantage	[76], [75],	[78],[74],[80],[82], [81],[79],[17]	[78], [77], [81], [79]	Open-Loop	Closed-Loop	Residential	Commercial	Transportation	Unknown
Types of Control Algorithm	GA	Works well with Continuouos & Discrete System	Expensive, Difficult to structure	Optimizing Fuzzy Controller [76]	Temperature Prediction Strategy [78]	Temperature Prediction Strategy [78]		[76]			[76]	[76]
	MPC: DMC/GPC	Relaxed control strategy for complex systems	Complex algorithm with larger variable count		Compares DMC and GPC, Supervised, Discrete Step Response & Second Layer Control [74],	Reducing computational time [77],		[74]	[81]	[74],[81]		
	Fuzzy	Great for Non-linear systems	Requires active input	Reduces overshoot & Transient response [75], Controls component of Apparatus [76],	First Layer Control [74], Manipulates Humidity & Temperature[80], Regulates heater damper, external air damper and fan via Mandani [82]			[74],[75],[76], [77],[80], [82], [16]		[74],	[77],[80], [82], [16]	[76]
	PPD	NA	NA		Satisfaction % Predictor [74]			[74],		[74]		
	ON/OFF	Simple to operate and implement	No variability, reduced efficiency		Control Box monitor occupant's Mobile phone[79]	Use bigdata [79]		[79]		[79]		
	PMV	Works well with thermal systems	Not suitable for dynamic systems	Sensation index (thermal Comfort) [76]	Function Index for parameters [74]	Passenger Thermal Comfort [77]		[74],[76]		[74]		[76]
	PSO & GRA	Efficient, robust & easy to implement	Higher complexity dimensionality & convergence challenges		Temperature Prediction Strategy [78]	Temperature Prediction Strategy [78]						
	PID	Easy ro implement & control	Multiple features & linearity challenges	Reduces overshoot & Transient response [75]	First layer control [74]			[74],[75],[77]		[74]	[77]	
Linearity	Linear	Simple Classification	Not suitable for non-binary		[78]	[81]		[81]				
	Non-Linear	higher dimensions	May be complex	[75],[76]	[74],[80],[81],[82]	[77]		[74],[75], [76]		[74]	[77]	[76]
Implementation	Simulation			[75],[76]	[74],[80],[81], [82]	[77],[79]						
	Prototype Trial				[79]							
	Combined				[78]							
Year, Country/Region				2008 China 2008 Iran 1994 USA	2011 Poland 2019 Canada 2017 S. Korea 2013 Croatia 2016 Italy 2012 Malaysia	2020 Germany 2019 Canada						

Another approach of HVAC control goes in details on how it achieved successful results such as reducing overshoot, transient response, and system fragility [75]. This approach uses fuzzy controller alongside PID controller to enhance the control strategy of temperature handling unit. In the initial start, the PID control resulted with hardly any overshoot or transient response, but as time goes on and set point is being manipulated it began to show overshoot and longer transient time and these affects continue to grow as time goes on. On the other hand, when introducing the fuzzy controlled approach, it maintains a steady output as time goes on with very minimal transient response period and hardly any overshoot. It appears that it can maintain this quality of results for long period of time. This study was intended for industrial building air control units and can potentially be used for transportation vehicles. The disadvantage of this approach is that it does not use prediction or learns the occupant's behavior over time. It also did not factor in other variables that can come from transportation vehicles.

A study [76] was done in an automobile setting for HVAC control and passenger thermal control using PMV (Predicted Mean Vote) and GA (Genetic Algorithm). PMV also referred to as sensation index is utilized as a key parameter along with other parameters for fuzzy controller. The optimization is then performed by tuning fuzzy controller using the GA approach. The study goes in details on how it achieves optimal results that show good potential. While thermal control in a vehicle cabin can be difficult due to many environmental and behavior variables, the results concluded for thermal comfort in this study showed significant improvement while considered energy consumption and efficiency during ambient air temperature variation. However, the idea of using thermal comfort as feedback instead of actual preferred temperature may not be feasible at all times due to different reaction by different people.

A more modern passenger thermal control approach was studied to expand on battery electric vehicles [77]. While this recent study's ultimate focus is to increase efficiency by reducing HVAC energy consumption, it explores avenues for HVAC control approach to aid with energy consumption reduction. It proposed an MPC approach that approximates the non-linear control strategy using what is referred to as "linear-quadratic model predictive control". It was able to provide nearly similar results to nonlinear and reduce computational time. It has features like running in real time and ability to be integrated in parallel with the vehicle's control unit. In this article, the model PMV is also used to determine passenger comfort in the vehicle cabin. It also takes into consideration the outside temperature and humidity. Controlling the air exiting the evaporator is key as humidity needs to be maintained. Overall, an optimal control strategy is developed by creating a zone that maintains comfortable cabin temperature without the need for excessive mass air flow. In addition, energy consumption prediction is added to address long term energy storage evaluation. While the article goes in details of the algorithm, the results of the simulated approach prove to be successful and future work plans for implementation on a prototype vehicle. However, this study did not mention how it will differentiate between occupants and automatically adjust the thermal conditions to their individual preference.

A recent and yet interesting, improved HVAC intelligent controller using prediction is studied and tested for evaluation [78]. This approach was implemented for learning Horizon (LH) and Predicting Horizon (PH) using Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Greedy Algorithm (GRA). The experiment is done in a building environment inside a theater room. The data was collected for both summer and winter season to address both extremes. The study is done by performing fitting when learning by obtaining values via smart optimization, and it predicts outdoor temperature using intelligent approach mentioned above. The article describes the algorithm more in details, and it indicates that it achieved success using this methodology. It indicates that the case study shows GRA to be most successful. However, the study did not mention how this approach can be implemented in an automobile and/or how it will handle variables that may result from a moving vehicle. It does indicate plans for future work to expand on LH & PH.

A study for intelligent HVAC was conducted to experiment the usability of Internet of Things (IoT) in an effort to provide best user experience using new technology [79]. A sensor box is placed in each room and is setup to communicate with other device in the building such as Heater, AC, ventilator and other equipment that is equipped with Wi-Fi capability. The sensor placed in a given room, monitors the user's movement in a given area via their smart phone and controls the HVAC system to provide comfort to the user where they may be traveling within the building. This approach also addresses efficiency and safety because it turns off the HVAC system once the user leaves the room and would send alert messages if gas is detected anywhere in the environment. This is classified as an intelligent system because it can be operated autonomously by minimizing the need for user manual input. Plans for this study in the future will consist of advancing this feature to collect, analyze and process big data. This study did not mention how it would implement it in a vehicle nor did it consider variables that may result from moving vehicle. In addition, it did not mention anything about learning the occupant's behavior in an effort to prepare the room prior to entry.

In this paper [80] it explores the use of Fuzzy logic controller optimization for HVAC control and efficiency consumption. The study focuses on electric transportation vehicles but also implies that findings can be implemented in closed building as well. The way this optimization is conducted is that it manipulates the rate of humidity and air temperature output based on feedback from the passenger's compartment air condition for thermal comfort. This study was conducted using MatLab/Simulink models for optimization and evaluation. The results show that power consumption can be reduced by modifying the air humidity's equipment operation to minimal output but still provide acceptable comfort compartment conditions. However, controlling humidity alone is not enough to aid with energy consumption and comfortability as it takes slightly longer to fully divert from one humidity factor to the other when dealing with large magnitude scalability. In addition, this study did not mention how it will predict the humidity preference for each occupant and prepare the environment ahead of time.

From modeling predictive approaches to energy efficiency, one study conducted in Italy uses a logistic regression model to predict building occupancy to control the HVAC system [81]. This approach was used to forecast the building occupancy to provide a predictive idea of what temperature the HVAC should be controlled. This study was more focused on energy consumption and its efficiency levels. It reduces energy consumption when space not occupied and allowing it to shift towards ambient temperature. The algorithm was designed more for efficiency and luxury than anything else. It provides a penalty factor to balance between energy efficiency and comfort. The article concluded with simulation being able to reduce electricity consumption and increase occupancy comfort. While this is a good approach to maintain a steady temperature that is suitable for comfort and efficiency, it lacks to address the presence of new occupants and their preference in either boundary extremes of ambient temperature preference that may be outside the set interval designed by this system. It also does not address condition that may contribute during transportation.

Another study shows the use Fuzzy logic to control temperature and Humidity in vehicle's cabin [82]. It indicates that the simulation has been successful in the development of temperature and humidity control strategy for HVAC utilizing Fuzzy Logic Control, namely Mamdani-type. It regulates three components called heater damper, external air damper and fan. This is great for maintaining a set temperature and humidity in a vehicle cabin but still requires the user to interact with it for inputting the temperature settings. In addition, it does not learn overtime the user preference and be able to automatically prepare the environment settings nor does it identify the customer in the cabin. This approach is great for areas that have a large variability in preference because it can be manually dialed in routinely to best settings but once adjusted the technology's capability ends there. This would be called a smart system in the sense that it can control multiple variables to provide a suitable environment in terms of temperature and humidity. Genetic Algorithm is proposed for future development. Fuzzy Logic in this context is used to provide a nonlinear demand such as one detailed in an article that refined the output much closer to the occupant's demand [83]. It made it possible to have a nonlinear system which finds a middle point that a linear system cannot provide.

An intelligent approach to HVAC control was studied to determine the advantage of using a self-learning algorithm to understand the human behavior for HVAC vehicle cabin control settings [84]. It monitors the passengers control behavior and learns from it to determine the passenger's preference. Once enough data is collected it can automatically control the cabin temperature with aid of PMV to the passenger's preferred thermal settings. This smart control mechanism reduces and/or nearly eliminates the passenger's interaction with control setting. Motivated by other control strategy proposals [85], [86], [87], experiment was conducted and showed significant energy consumption reduction compared to two other different types of control algorithms (fuzzy PID and traditional on-off). Energy consumption was measured over a period of 5000 seconds and showed 2.89 kWh and 2.19 kWh consumed using traditional on/off and Fuzzy PID respectively while only 1.97 kWh consumed using SLPTC strategy. Simulation and experimental practice were also compared and showed results with very low error between them. Overall, while this experiment was successful and shows great potential, the author does encourage to investigate experimenting in extreme conditions. The Author also indicated further experiment will be conducted with deep learning and other variables. This author also did not mention how it may handle cases where two different passengers occupying the same vehicle at the same time with different temperature preference can be satisfied by this approach.

1.6 Previous Review of Control Techniques

This section of the survey looks at literature reviews in the space of intelligent HVAC control strategy that have been conducted in previous years and how they relate or build upon to what is currently being reviewed. The intent is to look at the most recent reviews in an effort to stay up to date on the latest technology that is value added to what is being achieved.

A review was conducted in 2017 for residential applications in Ontario Canada to evaluate the use Artificial Neural Networks (ANN) alongside Model Predictive Control (MPC) in an effort to optimize the HVAC control and increase efficiency [88]. ANN structure as shown in the figure 3 consists of three stages, input (data feed), Hidden layer (Data manipulation) and output (intended results). These books, reviews, articles [89], [90], [91], [92], [93], [94], [95], [96], [97] and many more have been published to detail or contribute to ANN. It reviews how Model Predictive Control (MPC) using ANN for opportunities perform a case study by introducing a new algorithm called BNMI (Best Network after Multiple Iteration. BNMI simply compares new training result to best previously recorded result and replaces it if its better. The case study uses historical data as a learning method for optimization and prediction of HVAC control. While a thorough review was conducted for ANN-MPC to point out that it has been used for different environments, the study indicates that the MPC was able to save a range of 6% to 73% of cost depending on the season. This large range margin is due to season changes, but the minimum cost save is significant enough to propose a business case for implementation. While this review was conducted for residential environments, there is an opportunity to integrate it into other environments such as transportation vehicles.

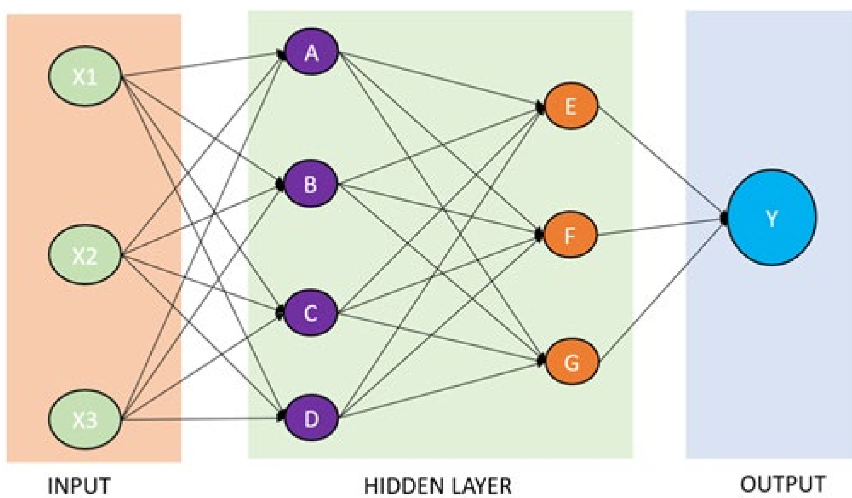

Figure 3: Artificial Neural Network (ANN) Structure

In this review conducted in 2017 by University Putra Malaysia, looks at nonlinear Fuzzy logic-based control techniques for HVAC [98]. This study investigates several methods for advantages and disadvantages for nonlinearity as well as introducing the Fuzzy Cognitive Map (FCM) method and details the advantages of this strategy. An FCM is a cognitive map that consists of elements and each element has sub-elements that further provide a more low-level information or relationship that dives deeper than that of layer before it [99]. The FCM approach is considered an intelligent method due to its ability to act like a decision tree in a sense that it can control better by not only distinguishing but also conducts a nonlinear control. This review evaluated several studies that show advantages and disadvantages in HVAC control some of which include relay control, closed loop, open loop, ANN, and fuzzy logic. The review indicated that while there are hard method and soft method; hard methods meaning the use of such control as relays for ON/OFF control and soft method meaning the use of software control which may include variability and most often closed loop; it finds that hybrid system would potentially be a best match for HVAC intelligent control. Hybrid system is the combination of both hard method and soft method. It suggests that with its conclusion the use of FCM as robust, simple, and efficient for real time control. Figure 4 gives a general example of the membership characteristics used in Fuzzy logic.

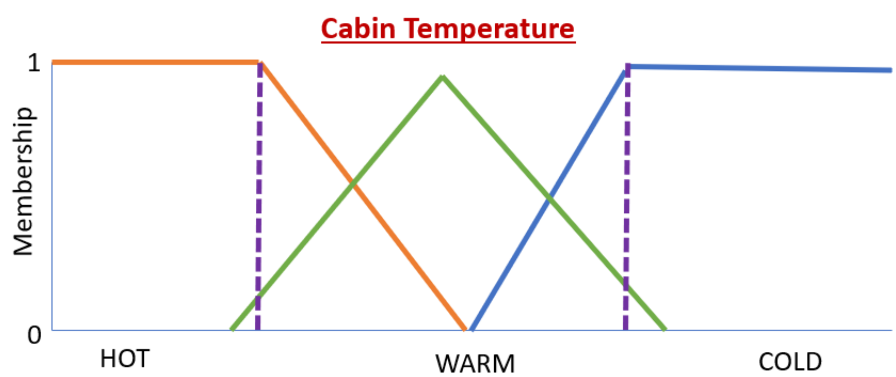

Figure 4: Fuzzy Logic Membership Class example

In a paper reviewing algorithm practice for HVAC systems [100] conducted in 2016 at Cardiff University in the UK details the different techniques in this field. The review evaluates multiple different approaches for algorithms utilized for HVAC control optimization and efficiency opportunity. While the review shows a wide variety of approaches, it hinted that there is no one single approach that can accommodate all internal and external variables affecting environment and comfortability. However, it did indicate that Artificial Neural Network (ANN) has been widely used due to its flexibility to serve in a larger number of applications. It goes further in details about categorizing the different type of approaches such as PID being standard but difficult to manipulate while fuzzy logic is more robust but requires human external inputs to redefine its output quality. It concluded with emphasis that many studies involved in HVAC are all working to increase efficiency and that their interest is more towards saving energy but also maintaining consumer comfort quality. It reveals that further future approach may be the focus of Multi-Agent Systems (MAS) as it finds a great number of interests in it moving forward.

In an article [101] conducted in Switzerland in 2016 to review the available options for HVAC control algorithms, mainly algorithms with prediction capabilities, it provided a comprehensive review that summarizes these techniques. It details algorithms currently being used and what advantages/disadvantages they provide. This review was mainly conducted for closed space settings such as building and rooms while also relying on outdoor temperature for some cases. While it discusses the control strategy, it also touches on how it provides occupant comfort alongside efficiency. Many of the approaches showed significant efficiency increase when applying prediction techniques during the control strategies. The review did not touch on how these approaches can be implemented in a vehicle's cabin while occupants are present, but it may be a suggestion to implement in the space of transportation. The future work with the evaluated algorithms and/or techniques may be able to increase efficiency and reduce energy consumption as more data become more available. It concludes that control features can further enhance with the growing amount of data collected and preserved.

An article-review conducted in 2020 addresses the adaptive and predictive control approaches for HVAC specifically in buildings [102]. This review concentrates on how elite HVAC control techniques can be an advantage in reducing energy cost for buildings that carry intelligent technology. Advanced and tradition control strategies reviewed included MPC, ANN and a number of other approaches. It indicates that while these are great control strategies and provide efficiency results, there are still implications that alter or affect the accuracy of measurement and overall results. This alteration would include location of measurement devices, consistency of input data and other outside variables that are not repeated cycle driven by nature. In addition, it touches on APCS, a fairly new concept in this area and is being heavily researched as there seems to a great potential for its use especially with the aid of cloud-based technology. The article concludes with encouraging the implementation of both cloud-based and local to compare and correct the variables that distinguish between final results of both methods. This review lacks to discuss whether these control strategies can be utilized in transportation vehicles.

Year	Reference	Control strategy covered	Optimization Algorithm Approach	Uniqueness	Efficiency	How it works
2017	[88]	ANN, MPC, MLP, RBF ANN, NARX, FeedForward ANN, ANFIS	GA, MOGA, Newton-Raphson, Interior-point, BaB, PSO, MOPSO, SPEA, SPEA-LS, S-MOPSO, Firefly,Harmony search	Best Network after Multiple Iteration (BNMI) and Supervisory MPC	6%-59% compared to single ANN training and 6%-73% compared FSP	Algorithm used to train ANN and choose the best trained ANN
2017	[98]	FCM, ANN, GA, On/Off, PID, Optimal, Robust, State-feedback, Compensation of static, Linearization by local feedback, Lyapunov, Backstepper, Sliding-mode, Relay control, Gain scheduling, Adaptive control, Fuzzy	Nonlinear, input-to-state linearizatoin, input-to-output Linearization	Fuzzy Cognitive Map (FCM)	Operate with a single device instead of two. Reduces Humidity from 80% to 40%	Intelligent Control approach for Nonlinear and MIMO HVAC systems.
2016	[100]	CI, ANN, SVM, Fuzzy, Pattern recognition, PID, Optimal, ANFIS, PI, GRNN, PCA, JAA, FDA, BN, MAS, ARTMAP ANN, Direct NN, AR-NN, clusturing	Stochastic, IA, Propulation based, Single individual, MAS, SI, PSO, ACO, Bees, EA, SA, Tabu search, GA, MOGA, GP, EP, ES, ED, Artificial bee colony, Baysian, FRB, MDP, LM BP, MLPNN	Comparison of Computational Intelligence (CI) in HVAC Revelaed energy efficiency is mainly studied in evolved/maturing countries	Nearly all methods reviewed in this paper had significant energy consumption savings	Reviewed HVAC control techniques in developed, developing and under developed countries
2016	[101]	ANN, MPC, MBPC, Fuzzy PD, Fuzzy, Optimal	MPC, Reinforcement Learning, Rule-based control, Cost function, Fuzzy Logic	Mainly focused on studies that use prediction alongside normal control strategy. Did not introduce a new approach.	Overall: Lowest is 13% Highest is 55%	Prepares room temperature prior to presence of occupants using prediction algorthms
2020	[102]	RL, ANN, Fuzzy Logic, Agent-based controls, PID, Gain-scheduling control, MPC, Robust control, on/off	Traditional and Advanced control Strategies, Adaptation Process and Prediction Variable	Focuses on advanced control strategies and area for improvement	There is potential for cost save but review encourages implementing the concept to determine efficiency	APCS controls dynamic process
2021	[103]	KNN, Markov Model, SVM, Proportional Model, Hybrid, Random Forest, Design Tree, LSTM, HMM, etc.	Evaluate occupancy score and adjust	Occupancy Based HVAC Control	Overall Results: Reviews show significant energy comsumption savings.	Predict Occupants and prepares environment

Table 5: Review Summary

A state-of-the-art review was recently published in June of 2021 to elaborate on HVAC control strategies using the presence of occupants in a building [103]. This review puts these control systems in categories to indicate their pros and cons in an effort to determine future potential challenges and development opportunities. The review agrees that implementing a system that automatically determines number of occupants instead of an individual inputting that data will result in more energy saving and potentially better comfort. On the other hand, it is indicated that thermal control based on occupancy presence can result in an initial thermal discomfort as the HVAC unit races to adjust when occupancy presence changes. Many of the approaches review were conducted with the sole purpose to save energy and still maintain quality comfort still leaves some challenges that needs to be addressed such as preparing the indoor thermal environment while keeping efficiency in mind. The review indicates there are future gaps that would potentially be key to improving this HVAC control approach. Potential future studies include during significant shift in occupancy presence, different Machine learning strategies, different environments and feedback from occupants. The review lacks to mention how these studies can be implemented in a transportation vehicle.

To summarize, all above are great reviews and provide important information about past, current, and potential future control strategies. The reviews show significant energy savings in most cases. In comparison, this literature survey used for the intelligent HVAC system is a review that also encompasses past reviews and attempts to identify areas of potential optimization opportunities. It makes it a unique review because it provides a diverse scope such historical background, occupant identification options, and attempts to integrates Linear Discriminant Analysis (LDA) alongside Kalman Decomposition (KD) for HVAC control. In addition, it reviews a variety of areas where these control methods/strategies have been studied and/or implemented with the intention of applying available opportunities in the automotive sector and points out efficiency number as shown in table 5 along with other optimization and uniqueness for each review.

1.7 LDA and KD Proposed Control Strategy

The proposal will assume it already have occupant's historical input and will be utilized to identify the driver's preference and be used as the learning data. Once they are identified, the system will then monitor how they control the HVAC and build a model using a learning method to automate the temperature setting based on their preference. Over time, this model will become more accurate and would potentially set the cabin temperature environment to the occupant's preference. This system can store countless number of users and build individual models whenever it recognizes an individual. A number of variables will be used as inputs such as outside temperature, in-cabin temperature, window open or closed, yearly season (i.e., winter, spring, summer, fall), latitude and other variables that may be discovered to be significant later in the study. It is believed that with today's transportation technology evolving rapidly towards the path of autonomous, this key feature in a vehicle can contribute to autonomous (hands-free) innovative implementation, which enables the occupants in the vehicle to focus on other activities while in the vehicle. In addition, it can contribute to the efficiency of energy consumption by the HVAC system.

The original plan was to use Linear Discriminant Analysis (LDA) to learn the user input and Kalman Decomposition to predict the user's best choice but with further studies it was determined to use the LDA as part of learning and predicting while KD can be used for maintaining temperature in real-time. The LDA algorithm can be used in this case to help isolate the wide band of user input to a certain interval that best suites the occupant's preference for cabin temperature. The LDA is selected in this case because it can take in many inputs and can separate them such as a classifier would do. This is critical in an effort to identify the driver and their preference. LDA has been used in many of applications for classification and optimization

[104], [105], [106], [107]. It is a reliable classifier because it's simple and robust. The LDA can rely on multiple variables to predict occupant's temperature setpoint such as:

- Season
- Temperature
- Location
- Weight
- Previously input setpoint
- And other feasible variables

The Kalman Decomposition (KD) can then be used to control the HVAC per the occupant's preference while taking into consideration other variables that may/may not be controllable and/or observable. The KD can involve a number of variables that may have uncertain characteristics such as controllability and observability to aid with executing a robust and more defined setpoint control of HVAC. There are a number of studies [108], [109], [110] that involve the use of Kalman Decomposition for systems that have uncertain characteristics and good progress. KD can be used to provide the final product for controllability in real time once LDA has defined the prediction. In the case of HVAC application, KD can be used based on its characteristics that consists of four variables that may exist within the system.

A. Controllable and observable: Cabin Temperature can be used for this variable because it is in an environment that can be monitored and controlled

B. Controllable and non-observable: Cabin Humidity can be used for this variable because it can be controlled but cannot be observed in some cases. There are humidity sensors that can be used but this proposal will only be within the scope of an economic vehicle. Some of the more expensive vehicles might be equipped with humidity sensors.

C. Non-controllable and observable: Outside Temperature will be used for this variable.

D. Non-controllable and non-observable: Occupant's clothing or attire can be used for this variable. Although there are ways that they can be measured but for the scope of this proposal the vehicle will not be equipped with such feature.With above variables taken into consideration it is believed that KD may be a good candidate to be utilized in the execution of this HVAC application and will aid with achieving good results. There is great potential for an HVAC controller utilizing both LDA and KD in an effort to provide occupant comfortability while maintaining energy efficiency and reducing energy consumption.

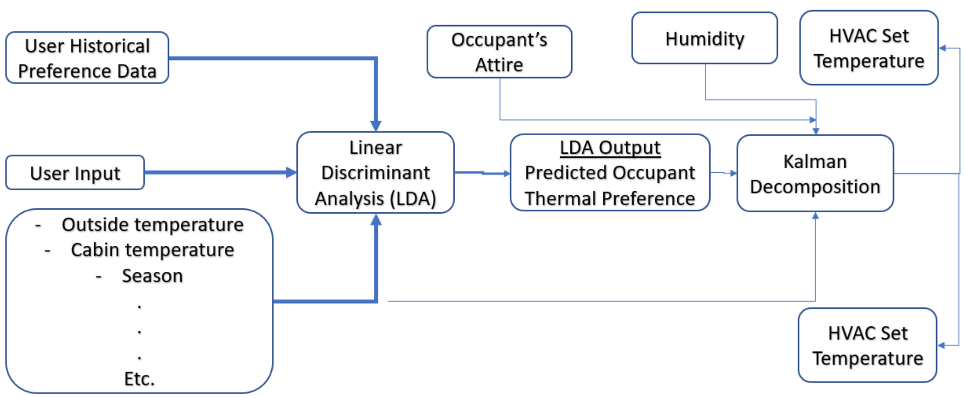

Figure 5: Proposed HVAC Control Process

It is believed that this feature as structured in figure 5 as whole is not yet integrated in vehicle and could become a new finding once the system is complete. If later found that this exact feature has been discovered previously, further studies will be conducted to uniquely distinguish it from other findings. The proposed research project appears to be promising and can be affective if implemented in a vehicle.

Chapter 2 : Linear Discriminant Analysis And Kalman Decomposition Algorithm

2.1 Linear Discriminant Analysis (LDA) And Where It Is Used

Linear Discriminant Analysis (LDA) is a conceptual algorithm used for separating supervised datasets. It is similar to Principal Component Analysis (PCA) but has slightly different approach. PCA distinguishes between variable by trying to find one with most variation while LDA distinguishes by trying to find maximum separation. LDA is mainly used in reducing dimensionality of dataset in an effort towards classification [111]. Often time dataset produced has too many attributes or features and therefore becomes cluttering to try to classify the dataset. LDA reduce dimensionality to make it simpler for the classification due to maximizing separation. LDA is widely used in many applications mainly to aid with classification by reducing dimensionality to allow for maximize of separation and isolate classes.

An application in the medical field can be a good example. LDA is used in the medical field to evaluate the dataset of previous patients to understand how to better diagnose current and future patients. An example is the use of LDA for feature selection for breast cancer dataset [112]. In this study, the features were reduced to four attributes with an accuracy score of 95%. Another case shows LDA being used for facial recognition with only minimum data [113]. Direct LDA is applied in this case to compare to other approaches when only minimum data is available, the average accuracy is approximately 75%. LDA has also been used for general classification problems [114] as well many other applications such as Mobile Robotics and data mining [115], [116], [117], [118], [119]. Other examples where LDA is used are Speechreading

[120] and signal processing [121]. In addition, LDA has been used for a variety of applications alongside other algorithms to produce an even more robust solution.

2.1.1 LDA Algorithm Concept

LDA consist of two different approached in terms of algorithm which depend on the classification variables weather its binary or multiclass [122], [123]. The reference tutorial/lecture details the LDA of dimensionality reduction for binary (two class) and multiclass. The main purpose of the algorithm is to take the inputs with multiple features and reduce them while maintaining classification quality. Equations in this section borrowed from A&M Texas University Lecture 10: Linear Discriminant Analysis). For two class LDA, it is assumed that covariance is equal

$$\mu_i = \frac{1}{N_1}\sum_{x\in\omega_i} x \ and \ \widetilde{\mu_i} = \frac{1}{N_i}\sum_{y\in\omega_i} y = \frac{1}{N_i}\sum_{x\in\omega_i} w^T x = w^T\mu_i \tag{1}$$

$$y = w^T x \tag{2}$$

$w^T x$ is the linear function, ω_i is the class, μ_1 is mean, μ_2 is covariance, X is the variable observed and T is the threshold of a given threshold boundary

$$J(w) = |\widetilde{\mu_1} - \tilde{\mu}_2| = |w^T(\mu_1 - \mu_2)| \tag{3}$$

The separation between classes is defined by the variance and Criterion function

$$\tilde{S}_i^2 = \sum_{y\in\omega_i}(y - \mu_i)^2 \quad , \ J(w) = \frac{|\tilde{\mu}_1 - \tilde{\mu}_2|^2}{\tilde{s}_1^2 + \tilde{s}_2^2} \qquad (4), (5)$$

where separation variable of output (y) can be expresses as

$$\tilde{s}_i^2 = \sum_{y\in\omega_i}(y-\tilde{\mu}_i)^2 = \sum_{x\in\omega_i}(w^T X - w^T\mu_i)^2 = \sum_{x\in\omega_i} w^T(X-\mu_i)(x-\mu_i)^T w = w^T S_i w$$

$$\tilde{s}_1^2 + \tilde{s}_2^2 = w^T S_w w \qquad (6), (7)$$

and means are expressed as follows

$$(\tilde{\mu}_1 - \tilde{\mu}_2)^2 = (w^T\mu_1 - w^T\mu_2)^2 = w^T(\mu_1-\mu_2)(\mu_1-\mu_2)^T w = w^T S_B w \qquad (8)$$

where S_W is separation matrix of features and S_B is separation between classes. As for Multiclass LDA, it is similar to Binary only now it is dealing with multiple outputs (y1, y2,….yn) compared to binary class shown above.

The feature separation is now described as

$$s_w = \sum_{i=1}^{C} S_i \qquad (9)$$

where $S_i = \sum_{x\in\omega_i}(x-\mu_i)(x-\mu_i)^T \; and \; \mu_i = \frac{1}{N_i}\sum_{x\in\omega_i} x$ (10)

where mean variables are defined as

$$\tilde{\mu}_i = \frac{1}{N_i}\sum_{y\in\omega_i} y\,, \tilde{S}_w = \sum_{i=1}^{c}\sum_{y=\omega_i}(y-\tilde{\mu}_i)(y-\tilde{\mu}_i)^T \qquad (11),(12)$$

$$\tilde{\mu} = \frac{1}{N}\sum_{\forall y} y\,, \tilde{S}_B = \sum_{i=1}^{c} N_i(\tilde{\mu}_i - \tilde{\mu})(\tilde{\mu}_i - \tilde{\mu})^T \qquad (13),(14)$$

and the separation between classes is described as

$S_B = \sum_{i=1}^{c} N_i(\mu_i-\mu)(\mu_i-\mu)^T$, where $\mu = \frac{1}{N}\sum_{\forall x} X = \frac{1}{N}\sum_{x\in\omega_i} N_i\,\mu_i$ (15),(16)

2.1.2 Why Choose LDA

LDA was selected for this application for a couple reason. LDA is a simple tool to apply and does not require extensive algorithm. Often LDA will require additional tools alongside to produce an even better result but not for scope of this study. In addition, Survey review concludes that LDA alongside Kalman Decomposition (KD) has not shown to be used for HVAC control in the automotive industry. Therefore, it was selected to explore how well it will work with predicting occupants utilizing the available features within the dataset prior to controlling the HVAC system via KD.

In an article published on Machine Learning Mastery [124]. It compares six different algorithms for accuracy including LDA. The figure 6 below shows a boxplot for accuracy and the author recommends LDA as part of the top two algorithms as shown below.

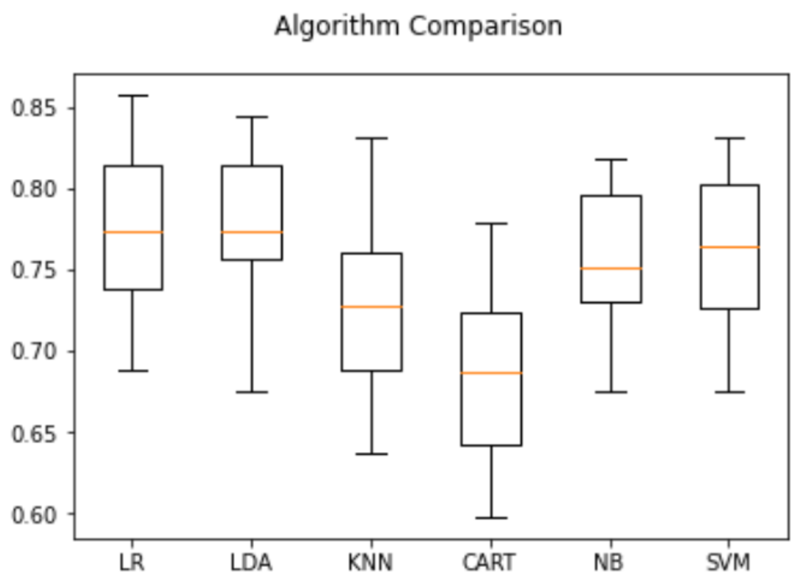

Figure 6: Algorithm Accuracy Comparison

Since implementation of algorithm are often faced with challenge such as speed and time. LDA algorithm runtime when measured is approximately 267ms while KD measures to be approximately 10,387ms. KD seem a bit higher than expected but that can be a factor of other variables not related to the algorithm itself such as machine being used to process the algorithm, amount of dataset, etc.

A study shows the comparison of machine learning algorithms [125]. It examines a number of models that are categorized by Model ID and shows some samples with memory usage between 354MB to 457MB. The studies of these algorithm's sample quantity vary and therefore makes it difficult to compare to this study. But overall, it the sample data used for this study is less than these mentioned and therefore memory is a lot less than the average. Memory is normally dictated by number of samples and/or other attributes that may require storage. Wallclock are also indicated to range from 129ms to 393ms. The LDA in this study may not be able to be compared to this study due to the uncertainty of discrepancy among these features used.

Another study shows a table that explores training and testing time for a variety of algorithms with similar features as the LDA study [126]. Table 6 shows the comparison with the some of the prediction algorithms captured to show the processing time. RAM and processor were also included to show the PC characteristics that executed the algorithm. Process time can vary depending on the processor and RAM. On average, the LDA score better than the average run time compared to other prediction algorithms.

Method	Training/Testing Time (ms)	Indoor temperature	Outside Temperature	Humidity	Set point	Motion	Seasonal	Wind Speed	Mont/ Day	Samples	RAM/ Processor Speed
Logistic regression	160.5	✓	✓	✓	✓	✓	✓			4,400	16GB 2.3 GHz
Markov model	201	✓	✓	✓	✓	✓	✓			4,400	16GB 2.3 GHz
Random forest	381	✓	✓	✓	✓	✓	✓			4,400	16GB 2.3 GHz
Hidden Markov model	245,000	✓	✓	✓	✓	✓	✓			4,400	16GB 2.3 GHz
Recurrent neural network	10,010	✓	✓	✓	✓	✓	✓			4,400	16GB 2.3 GHz
Linear Discriminant Analysis	267	✓	✓	✓	✓		✓	✓	✓	16,425	8GB 1.6 GHz

Table 6: Process time compared to other prediction algorithms with similar attributes

Time comparison between LDA/KD and algorithms examined in other studies show a wide band of runtime depending on what type and amount of data being processed. Overall, the time used for LDA seems to fall within range of other algorithms while KD seems to be a bit higher than others due to its nature of processing thousands of individual datasets. Using "tracemalloc" tool, the LDA/KD algorithm memory was to be measured. It shows a total of approximately 73MB of memory for LDA/KD combined. This memory amount usage shows positive signs for efficiency because the memory used is relatively low compared to other algorithms as shown in table 6 alongside other features for similar study. This memory approximation may change due to type of data or dataset count.

2.2 Kalman Decomposition (KD) And Where It Is Used

Kalman Decomposition is used to identify and control systems that have characteristics such as controllability and observability. The variables can also be both controllable and observable, controllable and non-observable, non-controllable and observable and non-controllable and non-observable. While it is shown that it has not been used as significant as LDA, this control method has been used in a number of applications such as linear quantum system [127] and other systems that are uncertain. In a separate study [128] conducted, it details how KD is used for what may be referred to as binary system. However, it does indicate that not all Boolean control network can be converted to KD. It has also been shown to be useful when integrated with other concepts to address linear systems [129], [130].

2.2.1 KD Control Algorithm Explained

Kalman Decomposition takes in Controllable, Observable, Uncontrollable and Unobservable in four different categories of the system input to be processed to have an output [131]. Matrix (17)(18) in this section borrowed from J.Braslavsky, The University of Newcastle.

- Controllable/Observable (Cabin Temperature)
- Controllable/Nonobservable (Cabin Humidity)
- Noncontrollable/Observable (Outside Temperature)
- Noncontrollable/Nonobservable (Occupant's attire)

The algorithm sequence is composed of a sequence steps and decision making during the decomposition and maintaining real-time cabin temperature control. As shown in the figure 7 below, input from the LDA is being brought into the system along with current outside temperature, Cabin Temperature and Humidity. The system decides if outside temperature has changed. If yes, it compares to the cabin temperature and preferred setpoint per predicted occupant. If no, it moves on to determine if cabin temperature is different than that of input data. If Cabin temperature does not match, then temperature is adjusted per occupant preferred setpoint. This process will continue to work in real time and adjust cabin temperature per occupant setpoint.

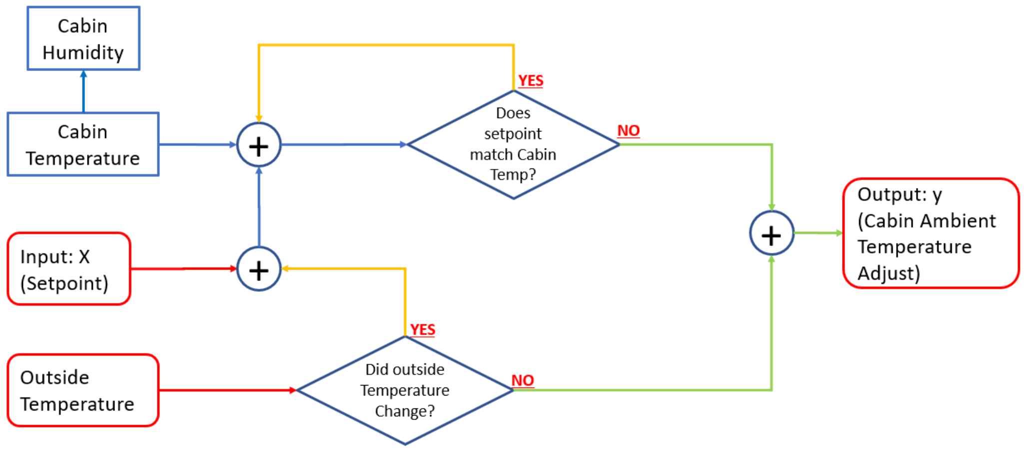

Figure 7: KD Algorithm Flow Chart

The structural flowchart in figure 8 below details how controllability and observability are realized within the system. It can be seen that 2 variables are controllable, and 2 others are not controllable.

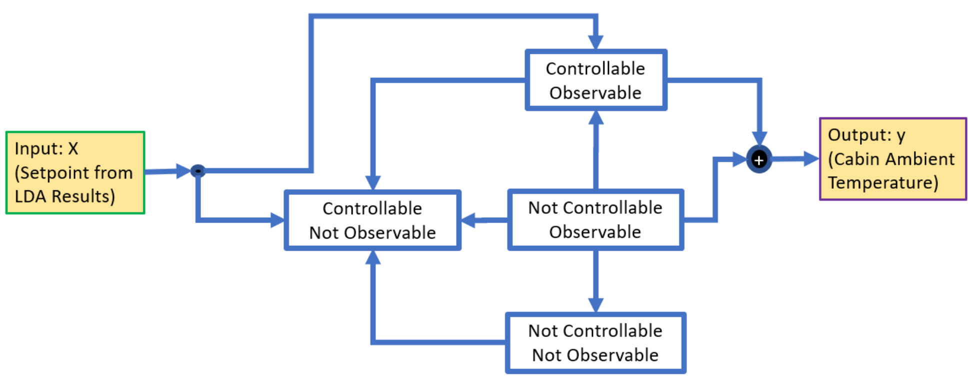

Figure 8: KD system Structure

The KD system is then constructed in the form below and later reduced to a smaller matrix:

$$\begin{bmatrix} \dot{\bar{x}}_{co} \\ \dot{\bar{x}}_{c\tilde{o}} \\ \dot{\bar{x}}_{\tilde{c}o} \\ \dot{\bar{x}}_{\tilde{c}\tilde{o}} \end{bmatrix} = \begin{bmatrix} \bar{A}_{co} & 0 & \bar{A}_{13} & 0 \\ \bar{A}_{21} & \bar{A}_{c\tilde{o}} & \bar{A}_{23} & \bar{A}_{24} \\ 0 & 0 & \bar{A}_{\tilde{c}o} & 0 \\ 0 & 0 & \bar{A}_{43} & \bar{A}_{\tilde{c}\tilde{o}} \end{bmatrix} \underbrace{\begin{bmatrix} \bar{x}_{co} \\ \bar{x}_{c\tilde{o}} \\ \bar{x}_{\tilde{c}o} \\ \bar{x}_{\tilde{c}\tilde{o}} \end{bmatrix}}_{\bar{x}} + \begin{bmatrix} \bar{B}_{co} \\ \bar{B}_{c\tilde{o}} \\ 0 \\ 0 \end{bmatrix} \mathbf{u}$$

$$y = \begin{bmatrix} \bar{C}_{co} & 0 & \bar{C}_{\tilde{c}o} & 0 \end{bmatrix} \bar{x} + \mathbf{D}\mathbf{u}$$

where A_{CO} is controllable and observable, $A_{C\underline{O}}$ is controllable but not observable, $A_{\underline{C}O}$ not controllable but observable and $A_{\underline{CO}}$ not controllable nor observable. Once, the matrix is reduced depending on the variable observability/controllability, it can compute the output control setpoint.

2.2.2 Why Choose KD

KD has been used for linear systems and other systems that are uncertain. KD was chosen because it has unique characteristics such as consideration of variables that may not be observable and/or controllable. This is important for this application because there are variables that are critical and must be considered even though they may not be observable and/or controllable. In addition, KD was chosen because it has ability to reduce dimensions' variables of matrix to eliminate non-value-added variables. In addition, based on the research conducted thus far within the scope of this application, it appeared that it has not been previously applied for vehicle's intelligent HVAC control system alongside LDA within this scope. This may be the first time it will be used in such application.

Chapter 3 : LDA and KD on HVAC Control Results

3.1 Historical Dataset

To train, test a model and allow for prediction to occur, historical dataset must be available for the model to learn and be used to test the algorithm. Some of the dataset was borrowed from the Weather Underground site (www.wunderground.com) that include one year's worth of data for 2020. It includes features such as daily maximum temperature, maximum wind speed and maximum Humidity. Other parameters such as Season, Setpoint and Occupant were manually generated to aid with dataset manipulation, allocation and use. Sample dataset shown in table 7.

	Season	Month	Day	MaxTempF	MaxHumid	MaxWindMPH	SetpointF	Occupant
0	1	1	1	38	92	18	71	1
1	1	1	2	47	74	20	70	1
2	1	1	3	45	93	9	68	1
3	1	1	4	38	96	15	72	1
4	1	1	5	39	96	16	72	1
...	...	...	...	...	...	...	...	...
5470	1	12	27	42	81	20	83	3
5471	1	12	28	45	89	20	86	3
5472	1	12	29	30	85	12	86	3
5473	1	12	30	44	89	21	84	3
5474	1	12	31	34	81	15	84	3

3.1.1 Dataset Explained

Season: This parameter is used to identify Winter (1), Spring (2), Summer (3) and Fall (4). It was determined to divide the seasons equally into three months each throughout the year with Spring being March-May. Summer being June-August. Fall being September-November and Winter being December, January and February. Dividing the dataset throughout the year helps coordinate the temperature swing while changing from one season to another and it also helps with training the model when reflecting occupant setpoint.

Setpoint: This parameter was generated using random values on certain intervals. It was assumed that there are three different occupants that drive this vehicle, and each have their own preference for cabin temperature. Occupant's data preference shown in table 8 in Fahrenheit.

	1	2	3	4
Occupant	**Winter**	**Spring**	**Summer**	**Fall**
ONE	68-72	63-67	58-62	63-67
TWO	73-77	73-77	73-77	73-77
THREE	83-87	78-82	68-72	78-82

Notice Occupant TWO prefers an average of 75F all year round while occupant ONE and THREE will change their preference to reflect season shift.

MaxTempF: Maximum outside temperature reached for that day.

MaxHumid: Maximum outside Humidity reached for that day.

MaxWindMPH: Maximum outside Wind speed in miles per hour for that day. The above outside parameters where raw data collect for year 2020. The data collected was for one year but had to be copied five times to simulate a five-year span for each occupant. Therefore, in total with all three occupants was 15 years which is equivalent to 5474 datasets. This is useful because LDA works better with more data.

3.2 LDA and Fit/Transform

For LDA, it is required to identify which parameters are used for input and which are used for output. In this case, input (x) is outside temperature, outside humidity, day, month, season and occupant setpoint. The expected output is the Occupant. The first step in the process is to run the script for LDA to begin separation maximization and dimensionality reduction. In this case the dimensions were reduced to 3 components reflecting the three occupants involved in this study and then were transformed to 0,1 and 2. 0 for occupant ONE, 1 for occupant TWO and 2 for occupant THREE. A build-in algorithm was used for processing LDA that is provided by "sklearn" for Python coding language (see Appendix A for LDA and Appendix B for KD). It includes all required features to manipulate the algorithm per intended approach.

3.3 Training and Testing the Model

In order to execute prediction training must take place. An algorithm Model by "sklearn" was used in this case to split the dataset for training and testing the data after separation dimensional reduction via LDA. By default, the data is split into 75% training and 25% testing data. These ratios can be changed for other studies. After the data is split it runs through the training and fit.

3.4 Accuracy Score

After training, the separation and dimensionality, the model is being tested to understand how well it predicts which occupant preference to set the cabin temperature depending on other variables. Using the test data, the accuracy score results in approximately 79%. It can be seen in figure 9 how the model predicted the occupant versus actual occupant. The accuracy score of this occupant prediction approach may be lower in number than others that have been conducted in other studies but still scores above average when taking into consideration the algorithm complexity, sensors and amount of data required to execute the prediction method.

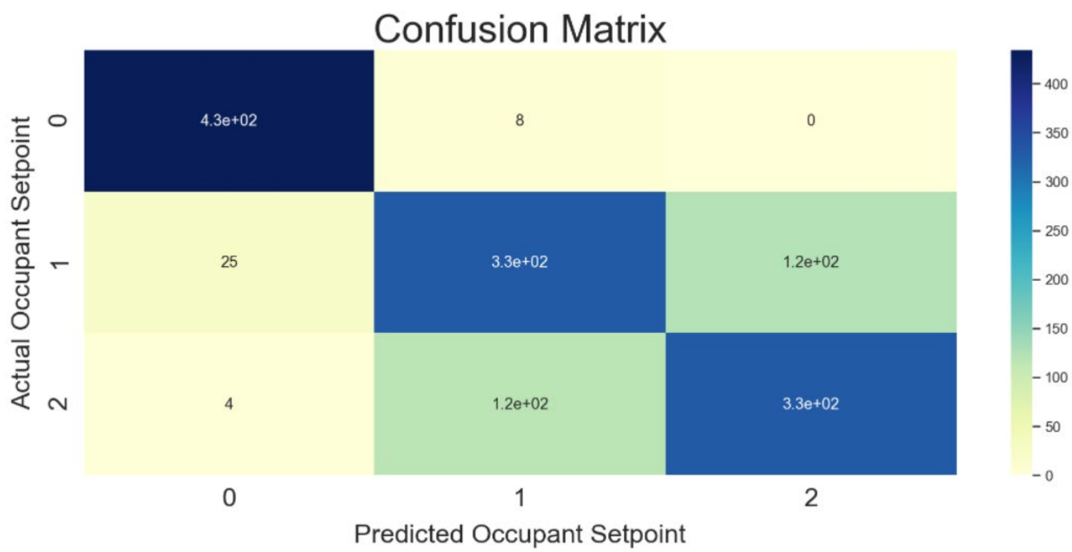

Figure 9: Confusion Matrix for 'Actual' versus 'Predicted'

3.5 LDA Performance Compared to Other Intelligent HVAC Control Algorithms

This application used multiple variables when applying LDA for occupancy prediction setpoint. In this section, a comparison with other algorithms used for occupancy prediction in the space of HVAC control is conducted to understand the accuracy score relative to other algorithms. Other algorithms compared may not be using all or the exact parameters and environment used in this study.

For example, a study [132] conducted for building space relied on parameters such as Indoor air temperature, Interior-wall temperature, and Exterior-wall core temperature along with other additional parameters. It compared three different approaches (GSPS, EM and uncertain basis) and shows accuracy to be more than 70%. Data was not available to trial it on LDA. This study collects data from a sensor in a room for certain period and/or intervals. It then processes the data using intended algorithm. This approach does not seem costly and could potentially be cost effective.

Another example that ran two different methodology using supervised and unsupervised rule-based machine learning technique [133] such as PCA with SVM, Bagging, LSTM or AdaBoost. This approach shows highest accuracy score of 98.3% for supervised and 97.6% for unsupervised. The parameters utilized were not clearly identified for supervised but the author did mention that all seasons should be considered which is an indication that this did not address all the extremes. In addition, unsupervised method includes parameters such as CO2, RH and Luminosity measurements. Implementation of such may not be complicated but can be expensive to have sensors that provide such data.

A study [134] shows to have achieved 95%-99% when selecting the appropriate classifier. Higher accuracy can be achieved but it comes with higher cost such as this because it is required to read CO2, humidity and other parameters within a building and not a vehicle. Clearly there are a variety of algorithms [135], [136], [137], [138], [139], [140], [141], [142], [143] that have high and low accuracy score for occupancy prediction. However, that does not mean that LDA is not capable of providing higher accuracy. LDA works better overtime with larger dataset and may work even better alongside other algorithm.

Figure 10 below details some control strategies that were used compared to LDA. It can be shown below that some may have higher accuracy rate than this study but that is mainly because they use more sophisticated and expensive instrumentation. In addition, some of the algorithm and setting may not be as simple as LDA. It appears that with the limited parameters and sensor used for an economical vehicle, the LDA studied here would potentially be classified as acceptable in its classification due to its advantages of being simple, robust and low cost.

Year	Reference	Accuracy Prediction strategy/Algorithm	Parameters/DataSet Communization	Prediction Accuracy	Advantage/Disadvantage compared to LDA (this study)	Overview of Process (Unique Integration)
2018	Occupancy-Based HVAC Control with Short-Term Occupancy Prediction Algorithms for Energy-Efficient Buildings	EM, FSA, GSPS, Stochastic	Indoor air temperature Interior-wall temperature Exterior-wall temperature Ambient temperature Solar Radiation Cooling Power Heating Power Internal heat gain	~70%	Advantage: Uses exterior/interior wall temperature, cooling/heating power and solar radiation. Disadvantage: Data segment is only 174 days (8352 samples per sensor). Random Occupance Schedule.	Implemented alongside another algorithm used for setpoint control. Does not use the exact sam variable as LDA (This study). Computes probability.
2020	Rule-based scheduling of air conditioning using occupancy forecasting	SVM, ANN, Bagging, AdaBoost, LSTM	Energy Consumption Indoor Temperature Relative Humidity Humidity Ratio CO2 concentration RH, luminosity Measures Holiday Schedule	98.3% (Supervised) 97.6% (Unsupervised)	Advantage: Uses CO2, RH & Luminosity. Evaluated random & non-random data. Identifies Holiday Schedule.	Integrate variables such as CO2, RH and Luminosity measurements. Historical Energy Consumption. Random/different Data used
2016	Accurate occupancy detection of an office room from light, temperature, humidity and CO2 measurements using statistical learning models	LDA, CART, Random Forest	Temperature (room) Humidity Luminosity measures CO2 Levels, Camera	95%-99%	Advantage: Uses CO2 & Luminosity. Uses Camera for occupant Defines Week status.	CO2 and Humidity. Luminosity & digital Camera. Photo stamp every minute Defines Weekend (0) & Weekday (1)
2013	Estimation of building occupancy levels through environmental signals deconvolution	NN, SVM	Temperature CO2 Concentration HVAC Actuation levels	88%	Advantage: CO2 Concentration HVAC actuation levels Disadvantage: Minimum Parameters count used	CO2 concentration, room temperature, and ventilation actuation signals
2009	Occupancy detection through an extensive environmental sensor network in an open-plan office building	Hidden Markov Models, SVM, NN	CO2 & CO TVOC Outside Temperature Dew point Small Particles (PM2.5) Luminosity Measures Relative Humdity (RH) Motion and Acoustic	80% (Average)	Advantage: 8 Additional variables are measure for variation. Disadvantage: Can be Exensive due to sensors measureing used. Data collected for ~4 months.	It is able to measure parameters of many different types of characteristics. Collected total data points ~60k for work week 8am-6pm.
2012	Information-theoretic environmental features selection for occupancy detection in open offices	RIG,	CO2, CO, TCOV Relative Humidity Acoustic, Camera Temperature Pressure Sensor Motion Sensor	37.39%-77.65%	Advantage: Uses motion sensor, Acoutstic, CO2,TCOV Pressure Sensors Disadvantage: May receive unnnecessary information due to space. Can be expensive.	Used special sensors such as motion sensor, Acoustics, CO2, CO, TCOV, Humidity and Camera
2010	An information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network	Hidden Markov Model, ANN, SVM,	CO2, CO, TVOC Small Particle (PM2.5) Acoustic, illumination Motion, temperature Humidity Internal Heat gains	73% (average)	Advantage: Uses motion sensor, Acoutstic, CO2,TCOV Pressure Sensors Disadvantage: Can be expensive.	Used special sensors such as motion sensor, Acoustics, CO2, CO, TCOV, Humidity and Camera
2011	Real-time occupancy detection using decision trees with multiple sensor types	Decision Tree	CO2 Computer current sensor Sound Sensor Light Sensor Motion Sensor	Up to ~98.4%	Advantage: ~41.8 million sample points collected Uses motion sensor & PC current sensor Disadvantage: Can be expensive. May be inaccurate if PC is ON	Uses Multiple same sensor which makes it expensive. Used light, sound, CO2, power use and motion sensors. ~41.8 million data points sampled
2011	Towards a sensor for detecting human presence and characterizing activity	Vision Based, Image recognition	Occupant's Body/Activity Recognition	97%	Advantage: Image Recognition Disadvantage: Background can be complex & may result in false detection. Difficult to detect when dark	Uses Camera for image recognition to identify human activity with monitored space
2012	Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations	RFID tag Count, KNN	Readers, Antennae Tags & Servers	88% (Stationary) 62% (Moving)	Advantage: Able to track via scanning tag Disadvantage: Cannot detect if 2 or more using the same tag	Uises RFID based tracking system
2012	A multi-sensor based occupancy estimation model for supporting demand driven HVAC operations	RBF Neural Network	Indoor Temperature CO2 Concentration Light, Sound & Motion Humidty Sensor	87.62% (Self Estimate) 64.83% (trained at other room)	Advantage: Efficient uniform approximation property Disadvantage: False reading due to light from window or noise from outside	Uses CO2, light, sound and motion. Study conduct for 20 days
2014	A systematic approach to occupancy modeling in ambient sensor-rich buildings	ANN, DT, KNN, NB, TAN, SVM	CO2, Door Status, Light, Motion, Temperature, Humidity, PIR, Sound	92.2%-98.2%	Advantage: Many types of detection sensors used Disadvantage: May be too expensive Too many sensors to immplement in economical space	Uses CO2, door status and light sensors
2021	Intelligent HVAC Control System (this study))	Linear Discriminant Analysis (LDA)	Season, Month, day, Temperature, Humidity, Wind Speed, Occupant setpoint	~79%	Advantage: Simple, Robust & inexpensive. Economical, Learns occupant behavor over time. Disadvantage: Requires historical data to perform.	Uses Season classification & Wind speed along with other parameters

Figure 10: Other HVAC Control Strategies Compared to LDA

3.6 KD: Input Versus Output

Kalman Decomposition (KD) is used in this application to take inputs in real time and then use it to maintain HVAC control. Four key parameters are used shown in the flowchart in figure 11 for the KD application post LDA operation.

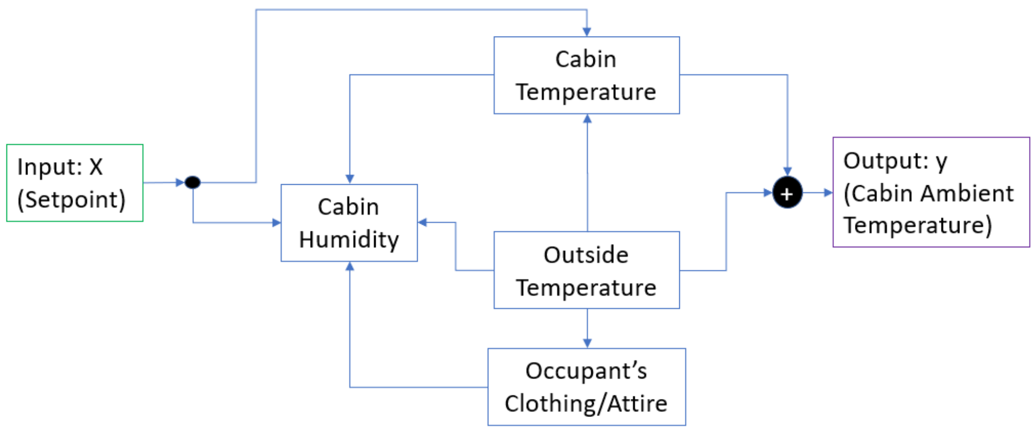

Figure 11: Overview of Input Variables to KD System

Input "X" is the setpoint by allocated by the occupant via LDA output. The KD takes in that input and controls the HVAC system in real time as the four parameters may change during transportation path. The KD will continue to adjust as the driver may be heading in a different route that is likely to have different humidity and/or outdoor temperature. in this case the cabin temperature and cabin humidity can be controlled to provide a more comfortable Cabin ambient air temperature (output "y").

Using a constructed KD algorithm, it was able to allocate which variable is controllable and observable. The KD algorithm is set manually to ensure the necessary variables are controllable and observable per architecture plan, then a normal loop can be used to structure and maintain cabin temperature.

3.7 Real Time KD Control Post LDA

In the case of KD, the parameters being used have been identified for which are controllable and/or observable as described in the sections above. Ultimately the system is reduced dimensionally to only variables that are viable to adjusting temperature. The process post LDA is to take the setpoint identified for certain occupant and have it as an input to the KD system which will be used to control the cabin environment as show in figure 12.

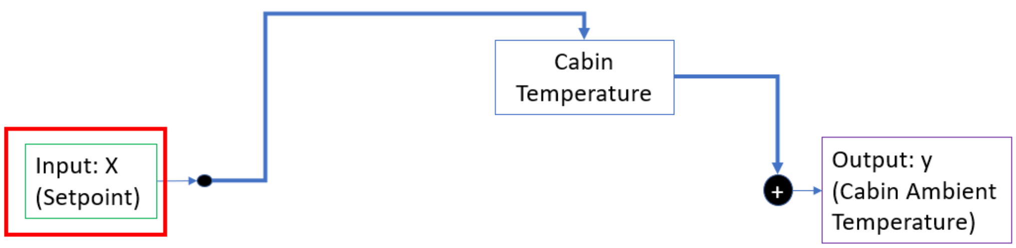

Figure 12: Controllable and Observable Parameter

The output controller will then be required to have a reference point to adjust accordingly relative to external temperature. Figure 13 illustrates how outside temperature is inserted into the system and where the outside temperature becomes a vital variable in the KD system.

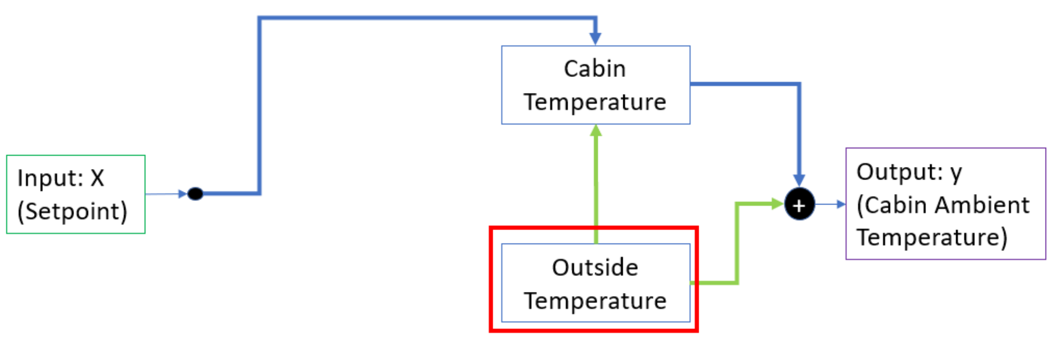

Figure 13: Noncontrollable and Observable Parameter

In this case the outside temperature is observable but not controllable and therefore can be used as the reference point as it affects the cabin temperature. Humidity is set to be controlled but not observed in this case due the scope of an economic vehicle. Controlling humidity is value added as it aids with comfort and can have significant impact depending on what season or time of year. As indicated in the figure 14 below, Humidity is not only affected by the input but can also be altered depending on outside temperature as well as cabin environment.

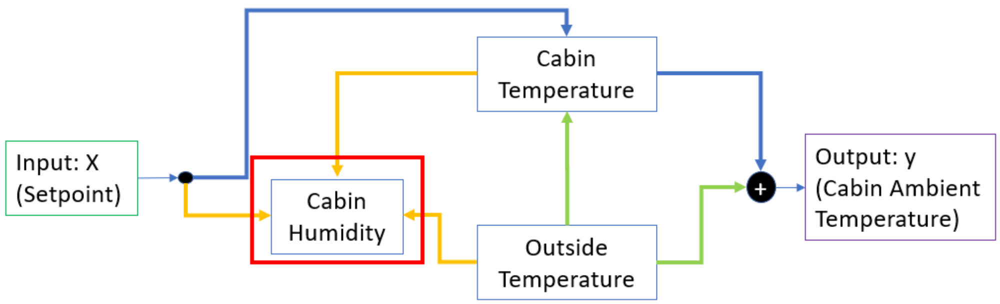

Figure 14: Controllable and Non-observable Parameter

The occupant's attire can have effects on comfortability if occupant wears something with higher attire density or lower attire density. This variable is neither observable nor controllable due to scope of this application, but the likely chance is that the occupant will maintain common attire density to address seasonal basis. Therefore, may not affect the transfer function in the end goal. KD's performance cannot be compared to other decomposition approaches at this time as it has not been evaluated in a real setting for this case.

Chapter 4 : Conclusion and Future Work

4.1 Conclusion

In conclusion, a study was conducted to experiment a new approach to control an intelligent HVAC system in an economical vehicle. A survey was performed to understand the technology and algorithms that have been conducted in the space of HVAC systems. It was found that a variety of control methods have been used in HVAC systems in office buildings, industrial areas, transportation and other areas. Many show great potential but also come with a cost. After review it was determined that the combination of LDA and KD have not been integrated in an HVAC system previously and therefore this combination was selected for the trial study. Using partially generated data and partially real data to train and test the model, the LDA for occupancy setpoint prediction results with an accuracy score of approximately 79%. This score could be rated above average in comparison to other applications that have used occupancy prediction due to other apparatuses in parallel that have been used. LDA is robust, easy to implement and low cost.

The KD is then evaluated conceptually to be post LDA and continue to maintain the cabin temperature in real time during transportation as outside environment continue to change with travel conditions and travel time. The KD takes in four key variables reduce dimensionality to certain variable such as cabin temperature and humidity that are controllable. From a theoretical standpoint the KD is manipulated to provide assign variable controllability and observability to intended parameters. These two tools integrated together can provide and economical system that may be implemented in a transportation vehicle.

4.2 Future Work

While the simulation seems to show acceptable results, there is still a lot of potential for future work in this application. One of the most important future works in this area is to implement it on an actual vehicle with diverse occupants setting to understand the effects of certain extremes. In addition, the LDA and KD together would potential drive better results if an additional classification algorithm is integrated to aid with separation. And finally, LDA works best with larger datasets. Adding more data may potentially increase its accuracy score and provide a more robust and competitive result.

The integration of both LDA and KD may be used in other applications where prediction and/or classification is used prior to real-time control of an uncertain system. Application that requires user identification such autonomous machines and device that operate per user. Other popular applications can be apparatuses such as ventilators, cleaning bots, sprinkler systems, autonomous lawn mower, automatic volt gates and many more. Some of these applications may require addition tools alongside LDA and KD for better/proper performance in areas where interaction complexity is significant.

Appendices

Appendix A: LDA Code (Python Jupyter Notebook)

```
#Linear Discrimanant Analysis (LDA)

#Import all necessary packages

import datetime

import time

import os

import sklearn # scikit-learn

import numpy as np

import pandas as pd

#Import LDA package

from sklearn.discriminant_analysis import

LinearDiscriminantAnalysis

#Read the file

hvac= pd.read_csv('./CleanInputData123.csv')

# Ignore warnings

import warnings

warnings.filterwarnings('ignore')

#Total sample of HVAC dataset

hvac

#Pairwise correlations
```

```
hvac.corr()

#Plotting Library

import matplotlib.pyplot as plt

%matplotlib inline

import seaborn as sns

# Appearance Configuration

%config InlineBackend.figure_format='retina'

sns.set() # Revert to matplotlib defaults

plt.rcParams['figure.figsize'] = (15, 6)

plt.rcParams['axes.labelpad'] = 10

sns.set_style("darkgrid")

# sns.set_context("poster", font_scale=1.0)

#Allocate Parameter to input and output

X=hvac[['MaxTempF','Season','Month','Day','MaxHumid','MaxWindMPH

','SetpointF','Occupant']]

y=hvac[['Occupant']]

#Applying LDA

from sklearn.discriminant_analysis import

LinearDiscriminantAnalysis

lda=LinearDiscriminantAnalysis(n_components=2)

cabin=lda.fit(X,y).transform(X)

#Sample Cabin array Values

cabin

#Setting up Split/Test for training
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test=train_test_split(X,y)
lda=LinearDiscriminantAnalysis(n_components=2)
lda=lda.fit(X_train,y_train)
#Prediction section
from sklearn.metrics import accuracy_score
y_pred = lda.predict(X_test)
#Check accuracy for training model
print(accuracy_score(y_test,y_pred)*100,'%')
#plot the confusion matrix
from sklearn.metrics import confusion_matrix
dt_pred = lda.predict(X_test)
ConfusionMatrix=confusion_matrix(y_test,dt_pred)
sns.heatmap(ConfusionMatrix, annot=True,cmap='YlGnBu')
plt.title('Confusion Matrix',fontsize=30)
plt.xlabel('Predicted Occupant Setpoint',fontsize=20)
plt.ylabel("Actual Occupant Setpoint",fontsize=20)
plt.tick_params(labelsize=20)
```

Appendix B: KD Code (Python Jupyter Notebook)

```
#Kalman Decomposition

#System Matrix Design

A=np.array([[71,0,0,0],[0,92,0,0],[0,0,38,0],[0,0,0,0]])

print(A)

#Input Matrix

B=np.array([[1],[1],[0],[0]])

print(B)

#Output Matrix wieghted

C=np.array([1,1,1,1])

print(C)

#Converting Arrays for manupilation

a2 = np.linalg.matrix_power(A, 2)

a3 = np.linalg.matrix_power(A, 3)

ab=np.dot(A,B)

a2b=np.dot(a2,B)

a3b=np.dot(a3,B)

ac=np.dot(A,C)

a2c=np.dot(a2,C)

a3c=np.dot(a3,C)

#Test for conrollability
```

```
bm = np.array([B,ab,a2b,a3b]);
print(bm)
#Check Controllability (Borrowed)
rankb = np.linalg.matrix_rank(bm)
print(rankb)
for i in range(4):
    if rankb[i] == 1:
        print("System is Controllable")
    elif rankb[i] != 1:
        print("System is Not Controllable")
#Allocation Parameter
c = np.array([C,ac,a2c,a3c]);
print(c)
#Check Controllability
rankc = np.linalg.matrix_rank(c)
rankc
if rankc==4:
    print("System is Observable")
else:
    print("System is not Observable")
```

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