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HEALTH AND USAGE MONITORING: AUTONOMOUS VEHICLES

A thesis

Submitted to the Faculty

of

Drexel University

by

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In Partial Fulfillment of the
Requirements for the Degree
of
Master of Science: Mechanical Engineering and Mechanics

Faculty Advisor: Dr. John M. Lacontora

To Mom and Dad

ACKNOWLEDGEMENTS

I would first like to thank my advisor Dr. John M. Lacontora for giving me an opportunity to work under him. Your constant efforts and inputs in the area of health and usage monitoring, as seen in this thesis, has helped me achieve a good level of understanding in the subject matter competently. You have been a constant source of motivation and provided exceptional guidance throughout my research in order to complete my thesis successfully.

Next, I would like to thank my friends for the help and support they have complimented me with throughout my program. Your support made this a fun-loving experience.

Finally, I would like to thank my parents and family members for always having faith in me. It is their belief and understanding that has helped me gained confidence in every aspect of life.

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LIST OF ABBREVATIONS

HUMS – Health and Usage Monitoring Systems
FDR – Flight Data Recorder
RCM – Reliability Centered Maintenance
PM – Preventive maintenance
CBM – Condition based maintenance
PdM – Predictive maintenance
RTF – Real-time Failure
RTMM– Real time monitoring maintenance
RUL – Remaining Useful Life
ARMA– Auto-regressive Moving Average
PHM – Proportional Hazard Monitoring
ETTF – Estimated Time to Failure
SME – Subject Matter Expert
AV – Autonomous Vehicles
ImSS – Improved Safety Systems
ISS – Integrated
CACC – Cooperative adaptive cruise control
GPS – Global Positioning System
LIDAR – Light Detection and Ranging
ACC – Adaptive Cruise Control
ITS – Intelligent Transportation System
NHTSA – National Highway Transportation Safety Authority

ABSTRACT

This thesis presents a work in progress related to the use of Health and Usage Monitoring Systems (HUMS) data to actuate an adaptive control system on an autonomous vehicle operating in an Intelligent Transportation Systems (ITS). The autonomous passenger vehicle has rapidly matured from a speculative concept to a reality that is quickly appearing within our sightlines. Autonomous (also called self-driving, driverless, or robotic) vehicles have long been predicted in science fiction and discussed in popular science media. Recently, major corporations have announced plans to begin selling such vehicles in the near future, and some jurisdictions have passed legislation to allow such vehicles to operate legally on public roads.

Autonomous vehicles will be performing intelligent functions (navigation, maneuver, behavior, or task) by perceiving the environment and implementing a responsive action based on HUMS input. Once these vehicles begin to operate on public roads as a norm, safety and reliability becomes a major factor. The implementation or expanded use of HUMS can perceivably render these systems reliable and safe to operate in any environment or mode. This thesis also depicts a notational framework for HUMS in autonomous vehicles operating on ITS networks and future research needed to make this a reality.

Keywords: Health and Usage Monitoring System (HUMS), Reliability, Adaptive Systems, Prognostics, Autonomous Vehicle, Intelligent Transportation System

CHAPTER 1. INTRODUCTION

Today advanced Personal Transportation Systems (PTS) such as autonomous vehicle are currently in the applied research arena; Advanced vehicle health monitoring and maintenance technologies need to be advanced at same pace as the vehicles. This thesis is focused on the Intelligent Transportation Systems (ITS) and the implementation of HUMS, prognostics approach to deduce meaningful information and to predict the health of the system.

Autonomous vehicles have arrived in ITS's across the world but safety factors and applications related with the technology is still a concern for numerous countries. If developed accurately, HUMS can serve as a potential solution to recent safety concerns with autonomous vehicles. The primary goal of this research is to attain that level of accuracy to implement in real world scenarios.

The PTS research is interested in concentrating its research and development efforts in the following area:

- Study advanced diagnostics and prognostic systems to include HUMS and autonomous vehicles in ITS

- Develop and conduct data analysis for HUMS and ITS data (big data analysis for vehicles and fleet)

- Develop a framework for vehicle censored data analysis and reporting.

- Provide a research environment for the study and development of learning and performance support system for technical workers that will aid in support and maintenance of semi and fully autonomous vehicles, resulting in the enhancement of their skills, knowledge and abilities.

This will provide a world-class vehicle technology research and development effort that can leverage the best of government, industry and academia. This research will leverage existing research and development activities to transfer their findings into new products and services.

The autonomous car industry is on the rise the last few years. Various commercial and experimental autonomous vehicles are being continuously developed, and some of them have already qualified level 3, the second highest level of automated vehicle, of the ranking of National Highway Traffic Safety Administration (NHTSA)[1]. Despite the recent leaps in automated vehicle technology, accomplishing the full automation of cars, or level 4 of the NHTSA's classification, is still a significant challenge, as this level would require the automated vehicle to be so reliable and safe in all working conditions that human intervention is not needed. This level means the autonomous program must be able to make all decisions regarding the driving conditions, and to accomplish that, it is important and helpful to set up a monitoring and analyzing system that can accurately capture and supply the data of the conditions of the many components within an autonomous vehicle. The output of such system would be beneficial in not only the decision-making process of the automated driver, but also in the maintenance and performance evaluation of the vehicle. Such a system has already been developed and utilized in different helicopters, and is commonly known as Health and Usage Monitoring System (HUMS).

[1] NHTSA ranks the technology of automated vehicle into 5 levels based on the vehicle's capabilities and technology. Level 3 means Limited Self-Driving Automation, while Level 4 can be interpreted as Full Self-Driving Automation. Details regarding the classification are available on NHTSA's website at http://www.nhtsa.gov/About+NHTSA/Press+Releases/U.S.+Department+of+Transportation+Releases+Policy+on+Automated+Vehicle+Development

CHAPTER 2. BACKGROUND

Over the past decade, autonomous vehicles have been studied and developed for real world application. ITS, which was a concept during the same time frame is now becoming a reality, with capability to deploy models based on current research and developments. This form of technology has been growing interest in various sectors (academia, industry and government) since 2004. In order to bridge the gap between our current capabilities and framework models, the development of HUMS will enhance the logistics support capabilities. Studies have shown that maintenance and logistics personnel are motivated to support advanced vehicle technologies but lack the tools such as advanced diagnostic systems, performance support systems, and onboard vehicle health monitoring systems to meet the needs thus rendering this workforce ineffective when it counts.

Since 1993, members of the Intelligent Maintenance Systems (IMS) lab have been involved in developing systems that enhance the capabilities of maintenance technicians by developing onboard and appended diagnostic systems such as SmartDART (Smart Diagnostics and Repair Tool) and SmartMentor, as well as Electronic Performance Support Systems, such as LockTel [36]. These systems coupled with an active condition-based maintenance capability that includes HUMS and IMS applications could serve as a game changing enabler for maintaining complex systems (manned and unmanned vehicles) at an elevated operational availability while lowering life-cycle support cost.

With the arrival of the latest versions of on-board computer processors, sensors, and control systems vehicles, on-board processors and data collection can now be considered intelligent systems. These can be leveraged to perform multiple tasks and serve as the platform for the deployment of emerging vehicle health monitoring, diagnostic, and prognostics technologies and processes. Technologists, scientists and engineers around the globe are at the forefront of many emerging technologies, and at the heart of these advances are some innovative practices. It is also important to note that government laboratories and sponsored research activities can be leveraged to accelerate the development of these systems. There are many opportunities for transfer of technology from government labs and universities to accelerate the maturity of these technologies and processes through small business innovation.

HUMS was introduced and developed in the late 80s, early 90s as a solution to the low airworthiness of helicopter during these times. It originated from offshore oil and gas industry, but soon gained attention from the military and other commercial sectors with its benefits. HUMS is capable of monitoring the conditions and performances of mechanical components of an aircraft, including gearboxes, bearings, shafts, engines, etc. through the vibration data of these mechanical parts. Additionally, it can also interact directly with the control bus of the aircraft, and record parametric data from it for data-mining and analysis. Valuable insights and information could be obtained from this information. Benefits of HUMS have been obvious and consistent, for a wide range of areas like improving reliability and safety of aircraft, optimizing maintenance processes, cutting operating costs and developing knowledge bank for design purposes [2].

An aircraft's HUMS usually features an extensive and multifarious collection of sensors that capture and convert the conditions of the components and operating environments. Since HUMS was originally created to work with mechanical parts, the majority of the sensors in an aircraft HUMS system deals with vibration health monitoring (VHM). The process as flow in generic form can be described as, first, information from the sensors would be stored and filtered by an acquisition unit on board, which will also transfer the data to a dedicated remote station. Second, data will be analyzed onboard and on the ground to derive and predict important information regarding the health of the components of the aircraft, and its overall performance. Figure 1 demonstrates a basic summary of HUMS process [2].

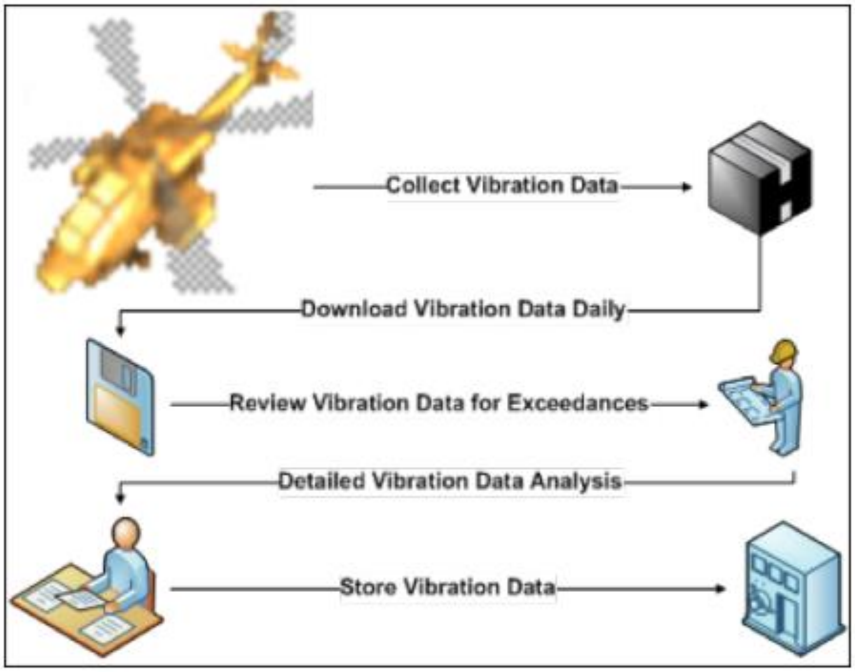

Figure 2 Basic HUMS process [2]

CHAPTER 3. Health and Usage Monitoring Systems (HUMS)

3.1 The Theory

The concept of HUMS is comparatively new. Since the industrial revolution, the perception of monitoring the health of structural and mechanical components has gained high significance. On the other hand, the notion of usage monitoring has been around for about half a century. The term system has been the latest addition to the fault identification process along with development of new algorithms for those processes. Data science plays as a backbone for this process. Since 1980's, the conception of data collection, data verification, health trending and sometimes usage calculation of various critical components came into play and the process is still maturing rapidly.

HUMS is a sensor-based monitoring system that enables Condition-Based Maintenance by measuring the health and performance of components. By continuously monitoring vibration at numerous points throughout the drivetrain, and pinpointing mechanical faults before they become catastrophic failures, HUMS provides actionable information that allows informed maintenance decisions [3].

Ever since they have been introduced in the aviation world, health and usage monitoring systems (HUMS) have gained traction and expanded from the offshore oil and gas industry to the military, unmanned aerial systems, and commercial and business operations. Previously they were called as 'North Sea HUMS' as they originated on helicopters servicing the North Sea oil platforms [1]. HUMS is designed to automatically monitor the health of mechanical components in various transportation systems. HUMS enable these systems to record structural and transmission usage, transmission vibrations, rotor track and balance information, and engine power assurance data. These devices can monitor the health of rotating components like gearboxes, engines, shafts, and bearings for different types of analysis (vibrations, usage and event). The intelligence gained from the use of HUMS allows maintainers and fleet operators to make informed decisions about driving/flying/sailing and maintain their systems [2].

In summary, HUMS capabilities can be listed as follows:

- Enhance safety
- Decrease maintenance burden

- Increase availability and readiness
- Reduce operating and support costs

3.2 Reliability Centered Maintenance (RCM): Maintenance Tactics

RCM is defined as the process of maintaining a complex system in a cost-effective manner. This analysis provides a structured framework for analyzing the functions and potential failures for a physical asset (such as an airplane, a manufacturing production line, etc.) with a focus on preserving system functions, rather than preserving equipment. RCM is used to develop scheduled maintenance plans that will provide an acceptable level of operability and risk in a cost-effective manner.

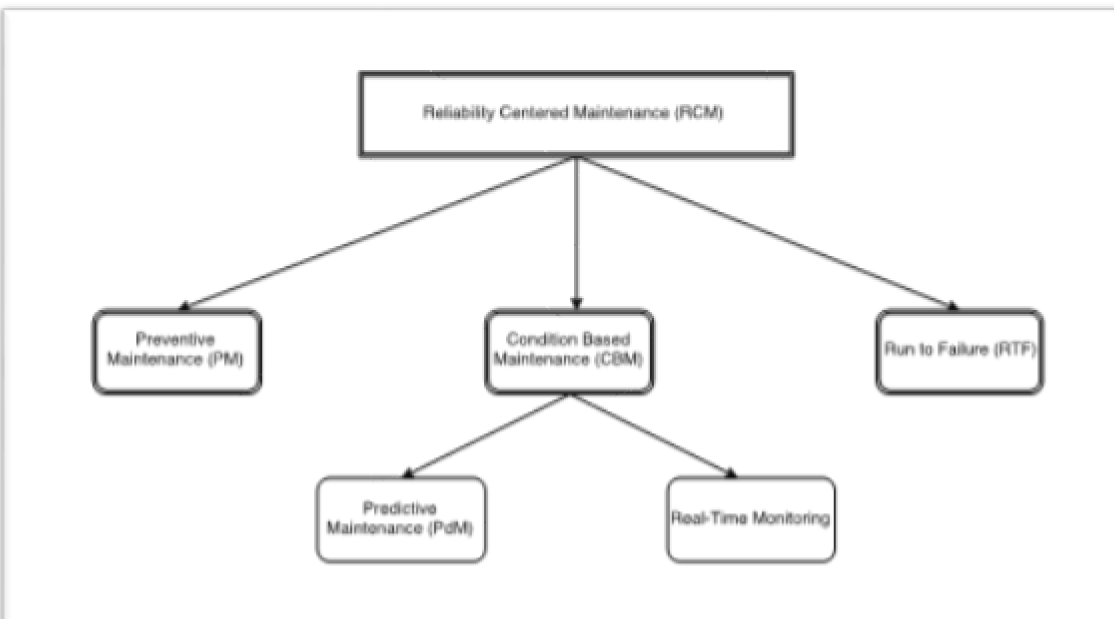

Figure 3.1 Elements of RCM Analysis

The terms reliability is the probability that a system will perform its intended function for a given period of time under the stated conditions. RCM focuses on this probability and gives a maintenance schema that will increase the reliability of the system. With increased reliability comes more uptime and less cost for maintenance. Nowlan and Heap [4] published a report titled

"Reliability-centered maintenance" after years of work and research on the topic and concluded that RCM is the way to achieve inherent safety and reliability capabilities at minimum cost.

The RCM analysis will be of minimal help when implemented in poor design with unreliable components. Thus, it is important that we apply this schema right from the early stages of development of a system to cash out all the available life form the components. According to the SAE JA1011 standard [5], the following are the seven questions that a maintenance schema should answer to be qualified as RCM,

1. What are the functions and associated desired standards of performance of the asset in its present operating context?
2. In what ways can it fail to function?
3. What causes each functional failure?
4. What happens when each failure occurs?
5. In what way does each failure matter?
6. What should be done to predict or prevent each failure?
7. What should be done if a suitable proactive task cannot be found?

The goals are to identify the most cost-effective and applicable maintenance techniques to minimize the risk and impact of failure in facility and utility equipment and systems. This allows systems and equipment functionality to be maintained in the most economical manner. Specific RCM objectives as stated by Nowlan and Heap [4] are:

- To ensure realization of the inherent safety and reliability levels of the equipment.
- To restore the equipment to these inherent levels when deterioration occurs.
- To obtain the information necessary for design improvement of those items whose inherent reliability proves to be inadequate.
- To accomplish these goals at a minimum total cost, including maintenance costs, support costs, and economic consequences of operational failures [6].

There are four outcomes from the RCM process are described below as seen in figure 3.1.

3.2.1 Preventive maintenance (PM)

PM is a fundamental, planned maintenance activity designed to improve equipment life and avoid any unplanned maintenance activity. This maintenance includes: systematic inspection, detection, correction, prevention of incipient failures, PM is the foundation of the entire maintenance strategy. Unless the PM program is effective, all subsequent maintenance strategies take longer to implement, incur higher costs, and have a higher probability of failure.

PM involves looking at the asset failure history, and instigating maintenance to fix it before there is a high probability of its failing. As defined in literature [7], actions performed on a time- or machine-run-based schedule that detect, preclude, or mitigate degradation of a component or system with the aim of sustaining or extending its useful life through controlling degradation to an acceptable level. As seen in table 3.1, it can be broken down into its pros and cons.

Advantages	Disadvantages
• Useful in many capital-intensive processes • Ensures high asset availability • Minimizes unplanned downtime • Increased component life cycle • For critical components, PM eliminates the severe consequences of failures	• Catastrophic failures still likely to occur • Labor Intensive • Includes performance of unneeded maintenance • Increases the cost of downtime

Table 3.1 PM Evaluations

For instance, in the case of changing the lubricant in a passenger car, typically, on an average people change their engine oil in their vehicles every 3,000 to 7,000 miles with no specific concern given to the actual condition and performance capability of the oil. If the owner of the car discounted the vehicle run time, and had the oil analyzed at some interval to determine its actual condition and lubrication properties, they might be able to extend the oil change until the vehicle had traveled to approximately 9,000 miles [9].

As seen in report [9], a detailed review of preventive maintenance approaches along with some characteristics can be described as follows:

- Failure rate limit policies, initiate maintenance when the system reaches a predetermined failure rate. State variables such as wear, stress, or damage are monitored to update the failure rate function. When the failure rate reaches the predetermined maintenance failure rate, the preventive maintenance activities are commenced.
- Sequential maintenance policies initiate maintenance according to unequal preventive maintenance time intervals. As the age of the component increases, the time between maintenance activities is reduced.
- Repair limit polices utilize a cost basis to determine the action taken when a component fails. When the component fails, the cost of repair is compared to the cost of replacement. The component will be repaired if the cost of repair is less than the cost to replace, otherwise the component is replaced.
- Repair number counting polices allow for a component to fail number of times before the component is replaced. The failures up to and including n-1 failure are mitigated with minimal repair.
- Repair number counting and reference polices are an enhancement to the process by adding an additional variable T that represents a positive operating time. Under the reference policy, the component is allowed to fail n times but is replaced at the n^{th} failure if the operational time has not reached the predetermined T value. If T has not been reached, the component is minimally repaired and replaced on the n+1 failure.
- Opportunistic maintenance policies address dependencies that occur in large systems. Failure of a component within a large system of components may require the removal of intact components to access the failed component. Given this situation, there is opportunity to replace or repair non-failed components according to criterion such a hazard rate or cost.
- Optimization of preventive maintenance policies is conducted by analyzing cost and system reliability measurements. The optimization approach generates preventive maintenance intervals by minimizing costs or ensuring that a desired system reliability is achieved.

3.2.2 Condition based maintenance (CBM)

CBM is a maintenance program that recommends actions based on the information collected through condition monitoring. For instance, it can intake maintenance techniques from real-time assessment of platform obtained from embedded sensors and measurements using in-built diagnostics systems [10]. CBM attempts to avoid unnecessary tasks by taking maintenance actions only when there is evidence of abnormal behaviors of a physical asset. A CBM program, if properly established and effectively implemented, can significantly reduce maintenance cost by reducing the number of unnecessary scheduled preventive maintenance operations.

3.2.2.1 Predictive maintenance (PdM)

Predictive maintenance can be described as: Measurements that detects the onset of system degradation (lower functional state), thereby allowing regular failure modes to be eliminated or controlled prior to any significant deterioration in the component physical state. The end result from a PdM technique is based on actual condition of the machine rather than preset maintenance schedule in the case of PM.

The aim of PdM can be stated as:

1. Predict when equipment failure might occur.
2. Prevent occurrence of the failure by performing maintenance.

Monitoring for future failure allows maintenance to be planned before the failure occurs. Ideally, PdM allows the maintenance frequency to be as low as possible to prevent unplanned reactive maintenance, without incurring costs associated with doing too much PM. As seen in table 3.2, PdM can be distinguished by its advantages and disadvantages [7].

Advantages	Disadvantages
• Increased component operational life/availability. • Allows for preemptive corrective actions. • Decrease in equipment or process downtime.	• Increased investment in diagnostic equipment. • Increased investment in staff training. • Savings potential not readily seen by management.

• Decrease in costs for parts and labor. • Better product quality. • Improved worker and environmental safety.	

Table 3.2 PdM Evaluations

On the other hand, maintenance decision support is a vital category considering various option available for maintenance. Selection of a sufficient and efficient decision support tool would be crucial to maintenance personnel's decisions on taking appropriate actions. Techniques for maintenance decision support in a CBM program can be divided into two main categories:

1. Diagnostics: fault diagnostics focuses on detection, isolation and identification of faults when they occur.
2. Prognostics: attempts to predict faults or failures before they occur.

Prognostics from its characteristics is superior among the two as it can prevent faults or failures, and in unavoidable circumstances help save extra unplanned maintenance cost. Nevertheless, both these techniques are complementary to each other as one fails and other provides meaningful conclusions. In addition, diagnostic is also helpful to improving prognostics in the way that diagnostic information can be useful for preparing more accurate event data and hence building better CBM model for prognostics [7].

3.2.2.2 Real-time monitoring maintenance (RTMM)

A smart maintenance technique can be created by integrating data from existing sensor technologies for cost control, logistics, purchasing, scheduling, and labor equipment maintenance. This maintenance schema can be regarded as RTMM. Over the years, industries have added digital communication networks, it became efficient to incorporate sensors not only for machine control but also data acquisition. Now, as industrial plants become more sophisticated with their data collection and as networking costs decrease there is a growing need to network an entire fleet. It is used in conjunction with CBM to continuously monitor the operating condition of machines in a plant. Communication networks have opened the door for CBM (PdM). By continuously monitoring a machine's condition, unforeseen problems can be identified and addressed [11].

3.2.3 Run to failure (also known as Corrective(planned) /Reactive (unplanned) maintenance) (RTF)

Maintenance tasks are initiated as a result of the observed or measured condition of an asset or system, before or after functional failure, to correct the problem. Reactive maintenance (Unplanned maintenance technique) is the ‘run it till it breaks’ maintenance mode. Usually the cost incurred from it are a lot higher. Corrective maintenance (planned maintenance technique) is implemented by the operator based on the designer’s recommendation. No actions or efforts are taken to maintain the equipment as the designer originally intended, to ensure design life is reached. As seen in table 3.2, RTF can be distinguished by its advantages and disadvantages [7].

Advantages	Disadvantages
• Low cost • Less staff	• Increased cost due to unplanned downtime of equipment • Increased labor cost • Cost involved with repair or replacement of equipment • Possible secondary equipment or process damage from equipment failure

Table 3.3 RTF Evaluations

3.3 Prognostics

Prognostics is the process in which the occurrence of some system event is predicted. It is conducted at a component/sub-component level. It is used to predict the time progression of a failure from its commencement to complete failure of a component. Prognostics and diagnostics are not the same but are related to each other. A journal article [12] proposes a simple delineation: diagnostics involves identifying and quantifying the damage that has occurred (and is thus retrospective in nature), while prognostics is concerned with trying to predict the damage that is yet to occur. Although diagnostics may provide useful business outputs on its own, prognostics relies on diagnostic outputs (for instance, fault indicators, degradation rates etc.) and therefore cannot be done in isolation.

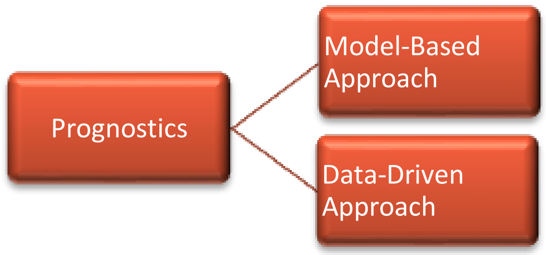

Figure 3.2 Prognostics Delineation

A prognostic output has two components:

(i) An ETTF, which is also referred to as remnant life or RUL

(ii) An associated confidence limit [13,14]

This confidence value is necessary, firstly, for the inbuilt uncertainty associated with the deterioration process. Secondly, due to the ambiguity regarding future operation of the machine. Finally, all the errors associated with both the diagnostic and prognostic methods being applied to gain meaningful deductions about the system. Business decisions based on prognostic information should therefore be based on the bounds of the RUL confidence interval rather than a specific value of expected life [13].

In summary, Prognostics enables adopting CBM strategies, instead of PM strategies. It is used to optimally schedule maintenance and planning for spare components. It can be used to reconfigure the system to avoid using the component before it fails by prolonging component life. This in return modifies how the component is utilized and can be generally classified into two types as show in figure 3.2,

3.3.1 Model-Based Prognostic

Model-based approaches to prognostic require specific failure mechanism knowledge and theory relevant to the monitored machine. It generally refers to approaches using models derived from first principles (e.g., physics-based). This implies that a thorough understanding is required of the system behavior in response to stress. This behavior can be described accurately and analytically. Physical models estimate an output for the remaining useful life of a system by solving a deterministic equation or set of equations derived from extensive empirical data. Some of this data will be converted into meaningful engineering knowledge, while the other data needs to be acquired through specific laboratory or field experimentation. Deriving physical models for a particular system will involve identifying numerous parameters like exact physical properties, corrosion rates and equation constants specific to that system. They can also be described without using any differential equations (state-space models) and solved accordingly [12].

Behavioral models are usually described using a series of dynamic, ordinary or partial differential equations that can then be solved with Lagrangian or Hamiltonian dynamics, approximation methods applied to partial differential equations or distributed models and other techniques [15]. Once a physical model is available, sensor measurements from the actual process are compared against outputs of the model. Differences between reality and the model are called residuals; large residuals are assumed to indicate a fault while small residuals occur under normal conditions like noise and modelling errors [16]. Thresholds can be defined to identify the presence and condition of faults or residuals used as inputs to other models. Residuals are calculated using parameter estimation, state-space methods or parity equations; the benefits of each are discussed in [18]. A general follow of process can be seen in figure 3.3,

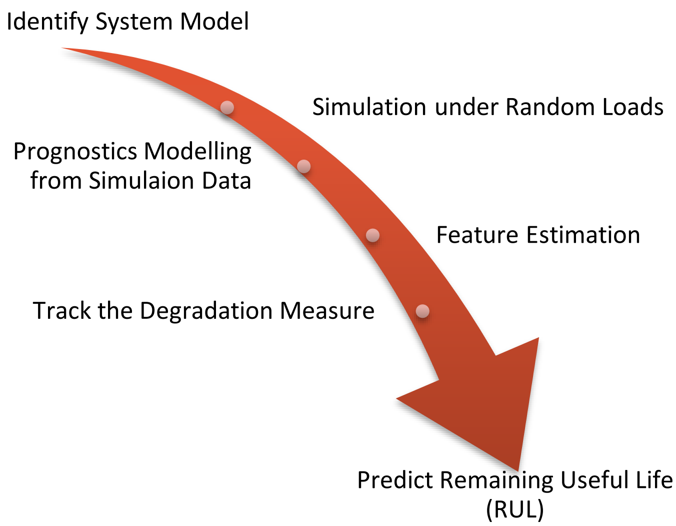

Figure 3.3 Model-Based Prognostics process, adapted from [18]

3.3.2 Data-Driven Prognostic

Data-driven approaches use real data derived from sensors or operator measures to approximate and track features revealing the degradation of components and to forecast the global behavior of a system. In many applications, measured input-output data is the major source for a deeper understanding of the system degradation. Data-driven technique can be divided into three categories:

i. Knowledge-based models: These assess the similarity between an observed situation and a databank of previously defined failures and deduce the life expectancy from previous events. Sub-categories include the following:

   a). Expert systems

   b). Fuzzy systems

ii. Life expectancy models: These determine the life expectancy of individual machine components with respect to the expected risk of deterioration under known operating conditions. Sub-categories are separated into statistical and stochastic models and include the following:

Stochastic models:

a). Aggregate reliability functions

b). Conditional probability methods

- Static Bayesian Networks:
- Dynamic Bayesian Networks:

Statistical models:

a). Trend extrapolation

b). Auto-regressive Moving Average (ARMA) models and variants

c). Proportional Hazards Modelling (PHM)

iii. Artificial Neural Networks: These compute an estimated output for the remaining useful life of a component/machine, directly or indirectly, from a mathematical representation of the component/system that has been derived from observation data rather than a physical understanding of the failure processes. They are further grouped into models used for:

a. Direct RUL forecasting

b. Parametric estimation for other models

Following figure 3.4, will aptly discretize both the models and in its sub-components.

Overview:

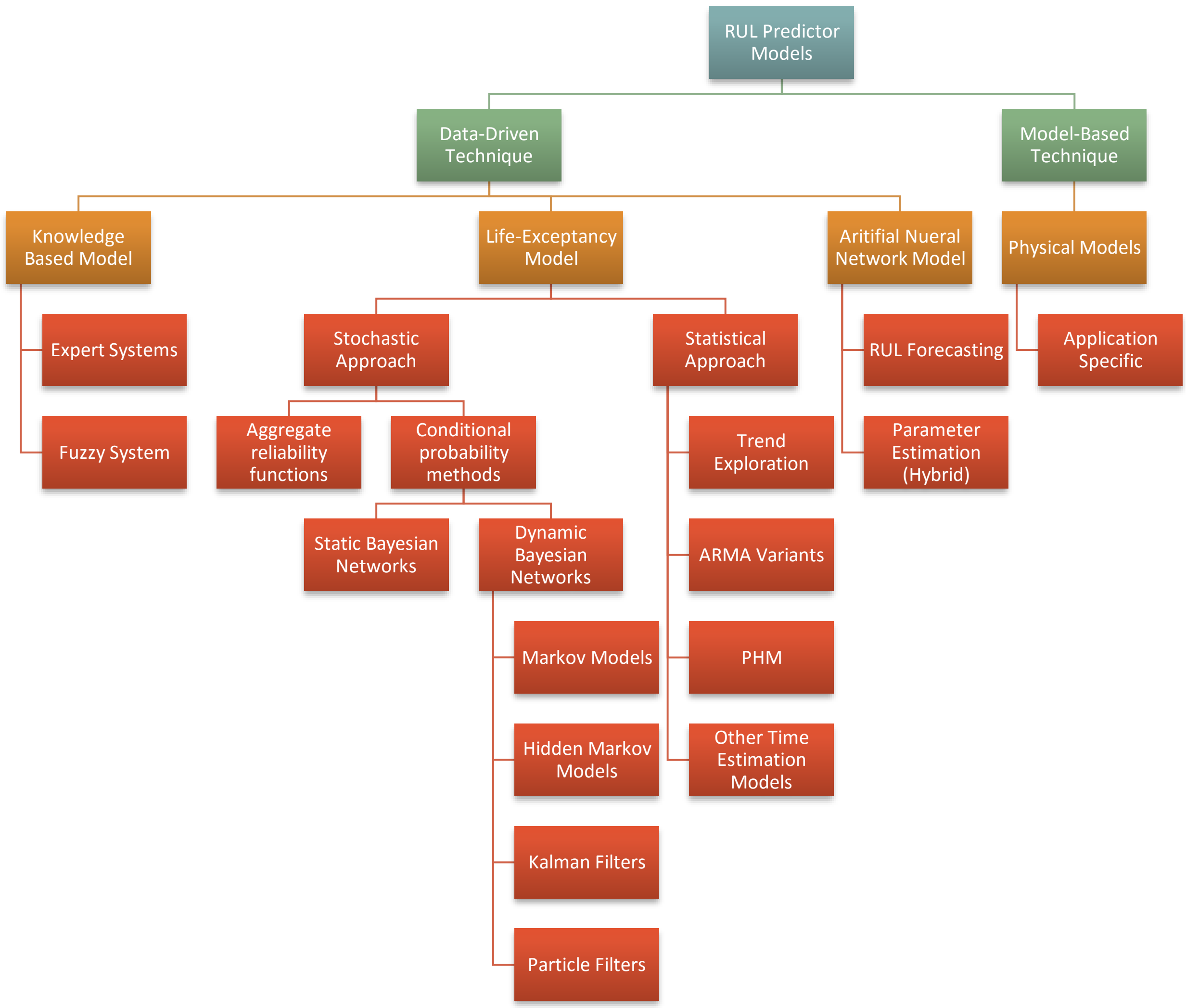

Figure 3.4 RUL Predictor Models

As seen in the figure above, there are numerous ways to achieve the goal. Hence, selection of a model becomes a vital process. There is not a single model with one size that fits all capability. Experienced data scientists are still reluctant on picking a specific model and guaranteeing its success. In order to do so, we need to apply the trial and error method. The following tables (3.4(a) – 3.4(c), adapted from [12]) will help ease the process, as it will provide useful information regarding when to consider and ignore a model according to its application.

Models	Consider	Ignore
• Expert System	○ Well understood, stable, narrow problem area; human experts available to develop the knowledge base; operating conditions are stable and predictable; simple precise queries to define potential faults is possible; only an approximate RUL estimate is required	○ No human experts available to define comprehensive set of rules; fault mechanisms are not well understood; operating conditions are highly variable; highly accurate or precise RUL estimates are required
• Fuzzy Systems	◊ One or more variables are continuous; and a mathematical model is not available or not feasible to implement; and data contains high levels of noise or uncertainty; and difficult to define exact queries that identify specific faults	◊ No human experts are available to define fuzzy rules; or input data is discrete and limited to a small number of options

Table 3.4(a) Knowledge Based Models General Application Criteria

Models	Consider	Ignore
❖ Aggregate Reliability Functions	○ Sample size is statistically significant; Small set of dominant failure modes; PDF is not exponential; and Reliability growth is not occurring; Condition monitoring data is not available; RUL prediction is predominantly used for overall maintenance management rather than tracking of a specific asset. so gradual escalation of warning levels is not required	○ Only a small number of failures can be attributed to individual failure modes; or significant number of possible failure modes that cannot be easily differentiated; Past operating conditions are not representative of current environment or usage; the specific asset is critical to plant safety or operations and warning is required prior to failure
❖ Conditional Probability Models ⇒ **Static Bayesian Networks** ⇒ **Dynamic Bayesian Network**	○ Incomplete, multivariate data available; and root causes of failure known; and process and plant configuration is relatively static or network is confirmed up to date; and modelling experts are available	○ Root causes of failure unknown; or expert plant and modelling knowledge unavailable; or training data unavailable

• Markov Model	○ Simple to develop and implement; incomplete, multivariate data available; and root causes of failure known; and process and plant configuration is relatively static or network is confirmed up to date; and relatively accurate and precise RUL estimate required	○ Repairable system; temporal measurement data as model inputs; sufficient data related to failure mode is not available for training; failure being modelled has more than one discrete stage
• Hidden Markov Model	○ Repairable systems; and root causes of failure known; failure being modelled has more than one discrete stage; temporal data to be used as model inputs relatively accurate and precise RUL required	○ Sufficient data related to failure mode is not available for training; suitable hardware for computation is not available
• Karman Filters	○ Multivariate posterior distribution; additive noise; condition monitoring data is available; relatively accurate and precise RUL estimate required	○ Multiplicative noise; single variable posterior distribution; covariate data is not available for the failures of interest.
• Particle Filters	○ Multivariate/non-standard posterior distribution; non-linear, non-Gaussian noise; Relatively accurate and precise RUL estimate required	○ Typical deterministic posterior distribution; or linear, Gaussian noise; or multiplicative noise; or single variable posterior distribution; or covariate data is not available for the failures of interest
Statistical Methods		
• Trend Extrapolation	○ Single defined failure mode associated with a single monitored parameter that can be described with a monotonic trend; and operating conditions are stable or do not affect monitored parameter; measurements are repeatable, reliable and not highly sensitive to	○ Incipient failure cannot be related to a simple measurable input; varying operating conditions that affect the measured parameter but are not related to failure; trend is not monotonic; data highly dependent on measurement process; data is subject to high levels of process or measurement noise; reliable confidence limits are

	measurement processes	required on the extrapolated RUL estimate
• ARMA Variants	○ Hazard rate is a linear relationship of covariates and noise; short-term predictions required; hazard rate is independent of age; measurement data is available for modelling and application but historical failure data is not	○ Hazard rate is not a linear relationship of covariates and noise; when historical or expert data is available in addition to measurement data; long term predictions are required; sufficiently large volume of data is not available for model construction and validation
• PHM	○ Times to failure are independent and identically distributed; covariates have a multiplicative effect on the baseline hazard rate; a number of covariates are available and required to describe change in risk; process represented by the covariates is stationary; associated covariate data is available for the failure modes being modelled; only the final RUL estimate and confidence limit is required.	○ Failures have not occurred previously or have no associated covariate data; hazard rate is not multiplicative; failures cannot be segregated into individual failure modes; covariates related to the failure modes being modelled cannot be measured; process represented by the covariates is non-stationary.

Table 3.4(b) Life-Expectancy Models General Application Criteria

Models	Consider	Ignore
• RUL Forecasting	○ Large amount of noisy, numerical, temporal data; and physical, statistical, deterministic model is not known, impractical to apply; an exact optimal answer for RUL is required	○ Data is complex and symbolic; Justification or physical extrapolation not required; Temporal inputs are not available; Minimal data is available for training
• Parameter Estimation	○ An RUL model (typically a physical model) is available but contains unknown parameters; large amount of noisy, numerical, temporal data; an exact optimal answer for RUL is required	○ Data is complex or symbolic; or minimal data is available for training

Table 3.4(c) Artificial Neural Network Models General Application Criteria

Models	Consider	Ignore
• Physical Based Model	○ Failure modes are well understood and defined; a physical model for each failure mode is available; operating conditions can be monitored and statistically represented; process/condition data is available; high accuracy and precision required in RUL prediction	○ A physical model is not available

Table 3.4(d) Physical Based Models General Application Criteria

In conclusion, the maintenance techniques stated above prove to be useful for a specific application. For the application HUMS in Autonomous Vehicles (AV), CBM (PdM) techniques proves to be of a higher value in comparison with the rest on the basis of their pros and cons (stated above). CBM itself as described above is broken down in to Diagnostics and Prognostics. The latter being of prime interest, there will be more focus on its vivid models and their applications. AV, in current times, has multiple sensors and programmed to various controls laws (especially, adaptive controls as a safety feature). Chapter 4, will discuss the same in detail.

3.4 Follow on

Engineers live in a world of measured data. The challenge is converting raw data into valuable information. Large data files are difficult to analyze because of long file length and high channel count. Further, analysis techniques vary with application – from diagnostics and prognostics analysis to durability analysis.

Prognostics is about forecasting failure based on actual product usage. A traditional maintenance approach based on hours or miles neglects one key variable: how the product is actually used.

Measuring field data allows engineers to quantify the severity of the service life, and then compare this severity with design targets. This forms the basis of a Health and Usage Maintenance System (HUMS) service approach by which maintenance schedules can be optimized based on real use.

There are various software that have developed a range of prognostic techniques that allows operators and fleet managers to really understand how their vehicles and assets are used. This includes analytical methods to measure the severity of field use with measured data, signal processing, and durability analysis techniques. These analyses can be further advanced in the field of automation to achieve safety and reliability of various owners and sensors.

CHAPTER 4. Autonomous Vehicles (AV)

4.1 Current State

An autonomous car is a vehicle that has the capability to guide itself without human support. This form of technology has been growing interest in various sectors (academia, industry and government) since 2004. Defense Advanced Research Projects Agency held a grand challenge to demonstrate the technical feasibility of AV navigating a 142 mile course in 2004. None of the vehicles at this challenge were able to achieve that goal. This led to boom in the research and development field for creating AV for human support. The tech giant, Google Inc., established itself as a loggerhead in the competition after successful attempts of applying autonomous technology to Toyota and Audi cars back in 2010. This kind of vehicle has become a concrete reality and may pave the way for future systems where computers take over the art of driving.

Generally, there are four primary categories upon which an AV technology is categorized

a. Perception: Vehicles use radar to detect obstacles, a laser ranging system to map the surroundings in three dimensions, and video cameras to identify objects such as traffic lights, construction signs, pedestrians and other vehicles.
b. Communication: Vehicle-to-vehicle (V2V) radios send signals between cars, trucks and infrastructure items such as traffic lights.
c. Location: Mapping software uses Global Positioning System (GPS) data to tell the car where it is in relation to roads, traffic signals, and other landmarks.
d. Route Planning: An on-board computer uses sensor data to plot a route that gets the car where it needs to go, while avoiding people, potholes and other vehicles.

The potential economic upside for taking driverless concept and moving it into reality is enormous. According to article [19], the potential of annual economic benefit from AV can be estimated to be roughly $211 billion, out of which $37 billion is derived form a 224-million-gallon reduction in petroleum-based fuels. All this may sound promising but the vital component of safety plays the driving force in ongoing research. Google cars on road driving test success has led to four states approving the legislature to have AV in operation in their states. On the other hand, seventeen states have failed to make decision on their legislature for the same because there is no clear indication of difficulties dealing with complex technical, legal, social and political issues surrounding vehicle automation. The figure 4.1 gives an estimate time line of advancement in the field of Autonomous vehicles and its related technology.

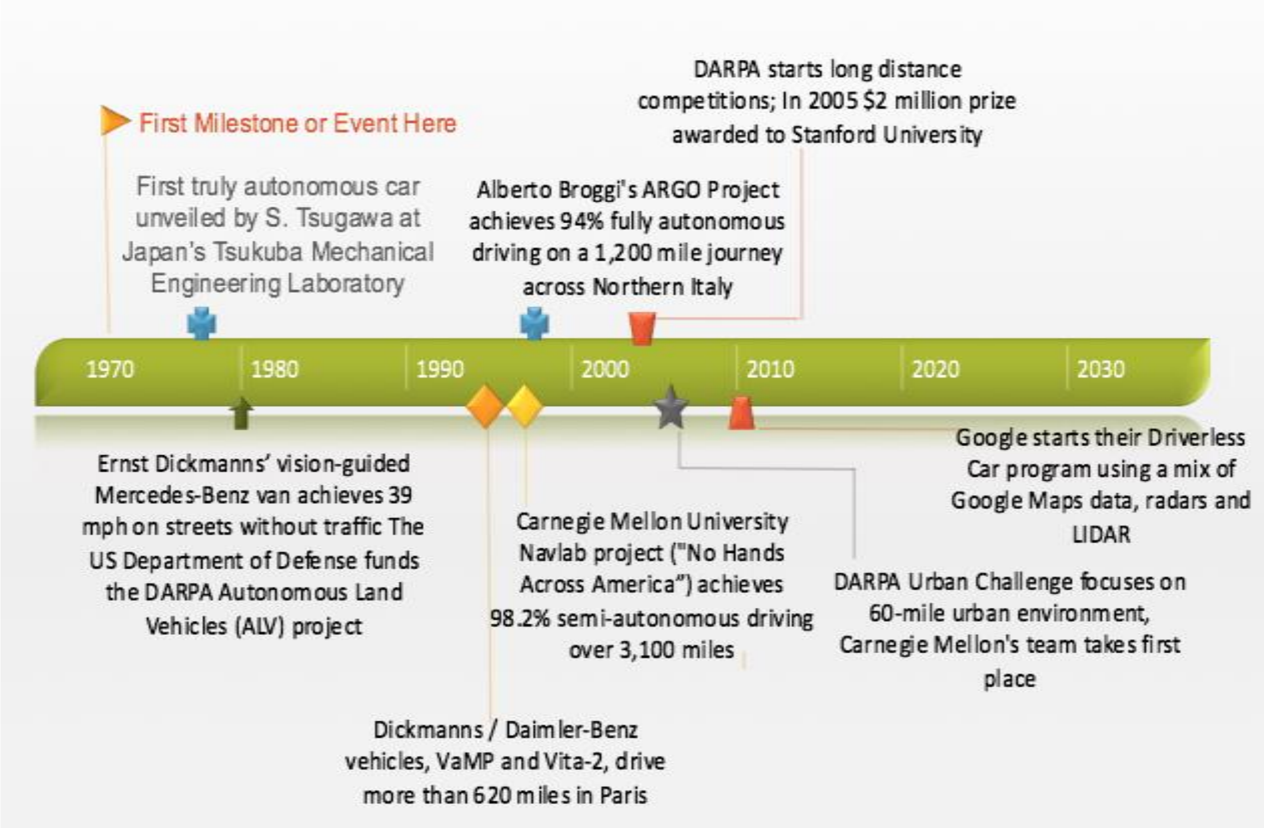

Figure 4.1 Historic Timeline Autonomous Vehicles [adapted from 28]

4.2 Safety Implementation

Preliminary data released today by the U.S. Department of Transportation's National Highway Traffic Safety Administration show a 7.7 percent increase in motor vehicle traffic deaths in 2015. An estimated 35,200 people died in 2015, rising from the 32,675 reported fatalities in 2014. "Every American should be able to drive, ride or walk to their destination safely, every time," said U.S. Transportation Secretary Anthony Foxx. "We are analyzing the data to determine what factors contributed to the increase in fatalities and at the same time, we are aggressively testing new safety technologies, new ways to improve driver behavior, and new ways to analyze the data we have, as we work with the entire road safety community to take this challenge head-on.” The seatbelt reminder technology had been introduced approximately sixty years ago. The technology added safety and convenience at that point of time but did not stop the rate of accidents from that time. Most of these accidents have been due to human error but these roadway collisions can be avoided with half a second’s warning, according to a recent study from intel. But autonomous technology is set to be so disruptive that it will take the driver out of the equation and redefine mobility and safety. The safety features available in current automobiles can be seen in figure 4.2

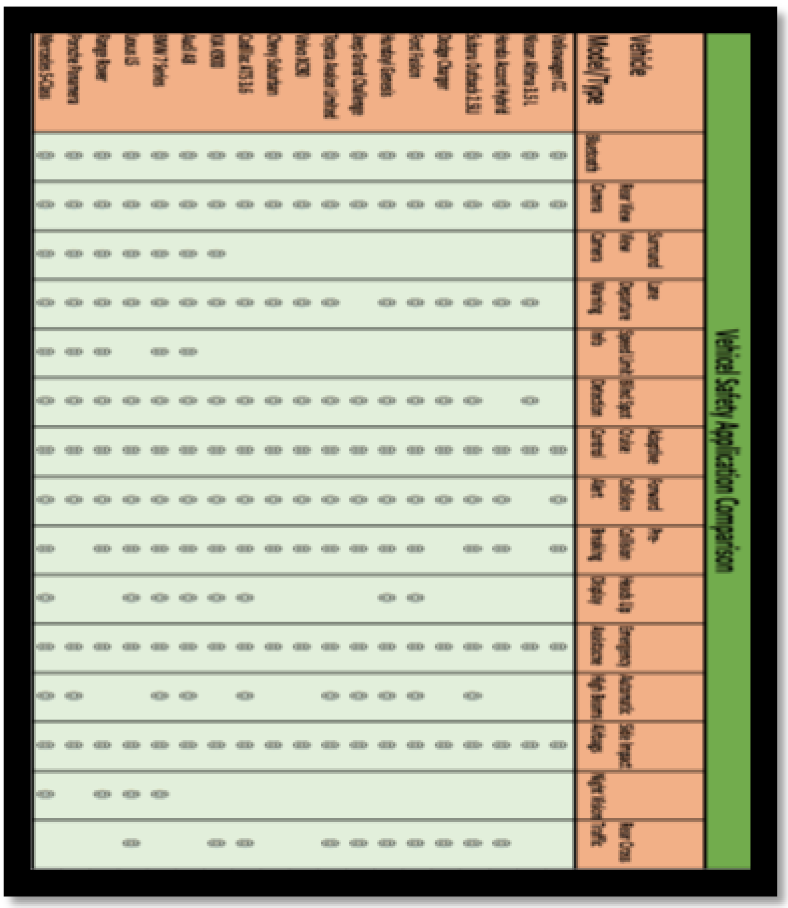

Figure 4.2 Vehicle Safety Application

The features, part of improved safety systems (ImSS) have included functions that provide meaningful information to assist drivers.

1. Forward collision warning
2. Video capability
3. Autopilot features
4. Lane-keep assistance
5. Blind-spot detection

These technological developments occurred at a much faster pace than the safety features brought about from 1950-2000, a period where seatbelts, airbags, antilock braking, and electronic stability control started becoming a part of the automotive world.

As discussed in the section earlier, advancement in safety features have been of great importance in AVs and their applications. National Highway Traffic Safety Administration (NHTSA) has been leading the research and development of this technology and making it operational reality. According to the article [20], Safety Model Deployment was conducted in Ann Harbor, MI where approximately 2,800 cars, trucks and transit buses took part in the deployment. There were approximately 300 cars which were full integrated of systems containing electronic devices (integrated safety systems, ISS) installed during vehicle production. Integrated safety systems are connected to proprietary data buses and provide highly accurate information using in-vehicle sensors. The ISS both broadcasts and receives Basic Safety Message (BSM) and can process the content through visual, sound, and/or haptic warning of received messages to alert the vehicle driver.

These BSMs are received through aftermarket safety devices which runs Vehcile-2-Vehicle (V2V) or Vechile-2-Interface (V2I) safety applications. All the systems were complemented with following safety features (as seen in table 4.2),

Safety Applications	Description
1. Forward Collision Warning (FCW)	Warns the driver if he/she fails to brake when a vehicle in the driver's path is stopped or traveling

	slower and there is a potential risk of collision.
2. Lane Change Warning/Blind Spot Warning (LCW/BSW)	Warns the driver when he/ she tries to change lanes if there is a car in the blind spot or an overtaking vehicle.
3. Electric Brake Light Warning (EEBL)	Notifies the driver about the vehicle ahead of it breaks for some reason.
4. Emergency Electric Brake Light Warning (EEBL)- Intersection Movement Assist (IMA)	Warns the driver when it is not safe to enter an intersection like instances where something is blocking the driver's view of opposing or crossing traffic.

Table 4.2 Safety Feature Applications, adapted from [20]

As seen from the table above, these are the current safety features applied to AV models during test. There is always room for improvement in the field of safety and its applications. While the above mentioned features sound promising, the future of safety features has a lot of value as well. Adaptive cruise control, lane centering, and pedestrian avoidance are some of them. We will focus on cruise control (Adaptive cruise control) and its current developments to provide aid to AV.

4.3 Controls Application in AV

Controls is considered to be the back bone of AV and their applications. There are various types of control techniques being implemented in the current models. Adaptive Cruise Control (ACC) is being considered the future of safety implication in model deployments created by NHTSA. ACC was first implement as by Mitsubishi Diamante in 1995 and followed by Toyota in 1996. It was used primarily to employ automotive LIDAR or radar sensors to measure the distance, velocity, and heading angle of preceding vehicles. This information is used to improve on the longitudinal control of conventional cruise control systems. When a free roadway is detected, the system behaves just like a conventional cruise control. When a slower preceding vehicle is detected the ACC systems follows at a safe driving distance until the situation changes [21]. The system works well on highways or in similar operation conditions.

The basis of ACC relies on the fundamentals of feedback controls. There are three important categories which drive the feedback system: speed control and force input, stopping and swerving. Table 4.3 provides more information about each of those types and its mathematical form used to formulate the output. Note: All these calculations are based from point mass consideration; this does make the evaluation process easier to understand with a tradeoff in precision.

Speed Control and Force Input	**Stopping**	**Swerving**
$m\ddot{x} + a\dot{x} = f_d - f_b$ where, m = Mass of the object $\ddot{x}$ = Acceleration/deceleration as a second-order time derivative of the displacement a = Viscous friction coefficient of road $\dot{x}$ = Velocity as a first-order time derivative of the displacement f_d = Driving Force f_b = brake force Let us consider the case of steady state, i.e., $\ddot{x}$=0 & $f_b = 0$, this concludes that $a\dot{x} = f_d$ or $\dot{x} = \frac{f_d}{a}$. This shows that velocity is directly proportional to the driving force divided by viscous friction and with the application of brake force, we will get the option of slowing down quicker.	Time to collision is an integral part of the stopping mechanism and is formally given in the text [22] as a quadratic form such as, $x(t) = x\,(t_o) + (t - t_o)\dot{x}(t_o) + (t - t_o)\ddot{x}(t_o)$ since we are considering the TTC, the distance travelled will be $x(t)$= 0. Applying the formula, we can easily derive, TTC. I.e., $TTC = \frac{-\dot{x}(t_o)\sqrt{\dot{x}(t_o)^2 - 4x\,(t_o)\ddot{x}(t_o)}}{2\ddot{x}(t_o)}$ Minimum stop time can now be calculated with time delay factor T_d where A_{max} and Jr_{max} denote maximum deceleration and jerk force. According to the standards defined text [23], the $T_{minimum}$ can be written in the form of, $T_b = \frac{A_{max}}{J_{max}} + T_d$ eventually resulting in the following form, $T_{minimum} = \frac{\dot{x}(T_d) - 0.5J_{max}(T_b - T_d)^2}{A_{max}} + T_d$	This technique is essential in terms of avoiding an obstacle in front of it and maneuvering itself from around it to safely pass the object. In recent studies conducted, AVs currently are tackling with a similar issue due to various form and nature of the obstacles. As stated in [24], LAD = $\sqrt{R^2 - (R - Y)^2} + \dot{x}T_{React} + c$ Equation above defines the Look Ahead Distance (LAD). $R_{roll} = \frac{2h\dot{x}^2}{wg}$ $R_{slide} = \frac{\dot{x}^2}{ig}$ where, R = radius Y = distance to travel in lateral direction to achieve clearance and go ahead signal $\dot{x}$ = velocity in longitudinal direction c = buffer region between the AV and obstacle T_{react} = Time required for the vehicle to react to an obstacle in the sensor range

		h = height of center of gravity w = width of obstacle i = friction between road and tire patches

Table 4.3 Feedback control laws and mathematical forms

ACC has its own algorithm and mathematical model, which is represented in report [22], where the author has compared three human driven models. Linear Car-follow Model, Linear Optimal Control Model, and Look-ahead Model. These can be presented as follows:

<u>ACC algorithm applied:</u>

$$\frac{d}{dt}p_n(t) = v_n(t)$$
$$\frac{d}{dt}\dot{p}_n(t) = a_n(t)$$

$$\frac{d}{dt}\ddot{p}_n(t) = b(\dot{p}_n, \ddot{p}_n) + a(\dot{p}_n)g_n(t)$$

where,

$$a(\dot{p}_n) = \frac{1}{m\tau(\dot{p}_n)}$$

$$b(\dot{p}_n, \ddot{p}_n) = -2\frac{kd_n}{m_n}\dot{p}_n\ddot{p}_n - \frac{1}{\tau_n(\dot{p}_n)}\left[\ddot{p}_n + \frac{kd_n}{m_n}\dot{p}_n{}^2 + \frac{d_{m_n}(\dot{p}_n)}{m_n}\right]$$

p_n = position of the nth vehicle
v_n = velocity of the nth vehicle
a_n = acceleration of the nth vehicle
m_n = mass of the nth vehicle
τ_n = nth vehicle's engine time constant
g_n = nth vehicle's engine input
k_{dn} = nth aerodynamic drag coefficient
d_{mn} = mechanical drag of the nth vehicle

Control laws applied are as follows:

$$g_n = \frac{1}{a(\dot{p}_n)}\left[c_n(t) - b(\dot{p}_n, \ddot{p}_n)\right]$$

where,

$c_n = c_p\delta_n(t) + c_v\dot{\delta}_n(t) + K_v v_n(t) + K_a a_n(t)$
$\delta_n(t) = y_{n-1}(t) - y_n - (L_n + S_{o_n} + \lambda_2 v_n(t))$
$\dot{\delta}_n(t) = v_{n-1}(t) - v_n - \lambda_2 a_n(t)$
L_n= length of the nth vehicle
S_{o_n}= initial headway
$\delta_n(t)$= deviation from desired headway
Cp, Cv, Kv, Ka = design constant

According to the authors context, there are a few criteria for stability of the system (explained in detail in the reference). This can be considered as one of the founding theories in the ACC. Currently, various car manufacturers have been implementing this as a safety technology to improve human driving experience.

4.4 Sensor and Hardware Application:

Complex systems such as an AV entirely depends on sensors for processing and making decision for its desired route. The sensor technology has evolved at a lighting fast pace to make these concepts a reality. Google Driverless Car, uses five core sensors to drive on a desired path.

1. **Radar technology:**

   It is primarily used for adaptive cruise control. The microwaves reflected from backside of the vehicles to the front side of the car behind it is used to adjust the speed. This type of technology does not use any satellite based information to set its control laws, it mainly uses on-board systems for processing the data. Co-operative adaptive cruise control (CACC) on the other hand uses satellite and roadside infrastructure to make a decision about its speed and avoid the obstacle. Figure 4.4(a) shows the radar technology in use.

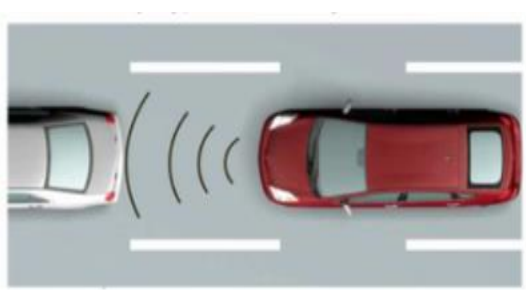

Figure 4.4(a) Radar technology in AV [adapted from 29]

2. **Ultrasound technology:**

Ultrasound has several characteristics which make it so useful and that have led to its use in many electronics applications. Firstly, it is inaudible to humans and therefore undetectable by the user. Secondly, ultrasound waves can be produced with high directivity. Thirdly, they are a compressional vibration of matter (usually air). Finally, they have a lower propagation speed than light or radio waves. The fact that ultrasound sensors are not audible to humans it is used for assisted parking as seen in figure 4.4(b). Reflected sound waves detect distance nearby objects.

Figure 4.4(b) Ultrasound technology in AV [adapted from 29]

3. **Cameras:**

This technology is mainly used for lane-keeping and back up assistance. Image processing software can detect lane-stripes, signs, stop lights, road signs, and other objects. Figure 4.4(c) shows where and how camera technology is implemented.

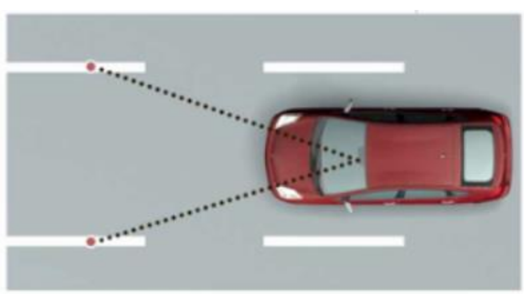

Figure 4.4(c) Camera technology in AV [adapted from 29]

4. **Navigational Aid:**

An autonomous car navigation system based on Global Positioning System (GPS) is a new and promising technology, which uses real time geographical data received from several

GPS satellites to calculate longitude, latitude, speed and course to help navigate a car. Accelerometers and wheel sensors help with navigation when satellite signals are blocked. Instruments and techniques such as the compass, sextant, LORAN radiolocation, dead reckoning are among those which have been used, with varying degrees of accuracy, consistency, and availability. Figure 4.4 (d) shows the GPS technology in use.

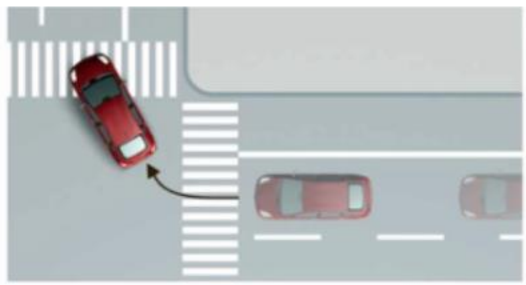

Figure 4.4 (d) GPS technology in AV [adapted from 29]

5. LIDAR:

One of the most integral, expensive, and noticeable pieces of equipment found in an autonomous vehicle is the roof-mounted device called LIDAR, which stands for Light Detection and Ranging, is a remote-sensing technology that measures and maps the distance to targets, as well as other property characteristics of objects in its path. LIDAR essentially maps its surroundings by illuminating its targets with laser light and then analyzing that light to create a high resolution digital image.

Google's autonomous vehicle research project uses a spinning range-finding unit as seen in figure 4.4(e). It has 64 lasers and receivers. The device creates detailed map of the car's surrounding as it moves. Software adds information from other sensors and compares the map with existing maps and notifies any differences.

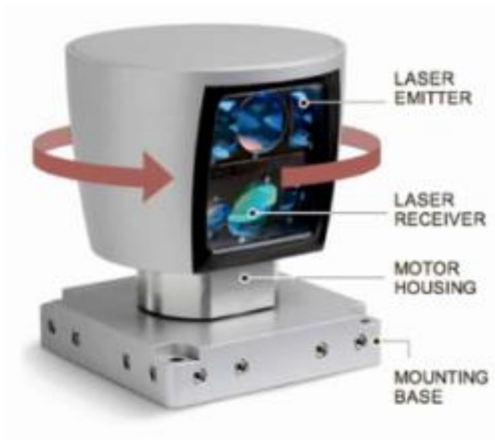

Figure 4.4(e) LIDAR technology in AV [adapted from 29]

4.5 Follow on

Autonomous cars will provide greater fuel efficiency from lighter vehicles and increased electrification of the car fleet, but many of the most important benefits to society will be in terms of safety. Vehicles will eventually have control modules and sensors to allow them to communicate with each other and infrastructure to avoid hazards and accidents. How quickly the U.S. and other countries reach deep penetration of autonomy depends a lot on how the incumbents the auto industry adopt and how successful new companies such as Google are at dispensing their technology. The car itself is extremely innovative, technical, and advanced. In order to properly design the software behind the car and the appropriate measures to take in any given situation, the Google engineers mined data from different cars; in total, they monitored over 200,000 miles of driving. After analyzing their findings, the engineers came to the conclusion that people do not, in reality, follow the rules of the road. And thus, Google thought it would be best to have the cars respond to many of the unwritten laws of the road that people are more unlikely to follow. The next decade provides a lot of promise in this area.

HUMS is a type of Vibration Health Monitoring (VHM) technique. To successfully implement HUMS system in automotive vehicles, a comprehensive understanding of the failure modes of the car components is required. Based on this information, a system should consist of data processing and collecting unit, and application specific sensors would be developed. However, current car's

ECU lack the data analyzing and processing functions of aircraft HUMS controller; therefore, either an accessory unit will be added to the existing control systems of auto vehicles, or the data from ECU will be transmitted to a different location capable of doing the analyses. Additionally, to increase the performance of automobile HUMS system, it is a good idea to divide the car components into modularized categories, which ease the data analyses processes, and isolate the monitoring aspect of the system while still maintaining a comprehensive evaluation of the vehicles [35]

CHAPTER 5. Intelligent Transportation System

5.1 The Concept

The term Intelligent Transportation Systems (ITS) refers to information and communication technology, applied to transport infrastructure and vehicles, that improve transport outcomes such as: Transport Safety, Transport Productivity, Travel Reliability, Informed Travel Choices, Social Equity, Environmental Performance and Network Operation Resilience.

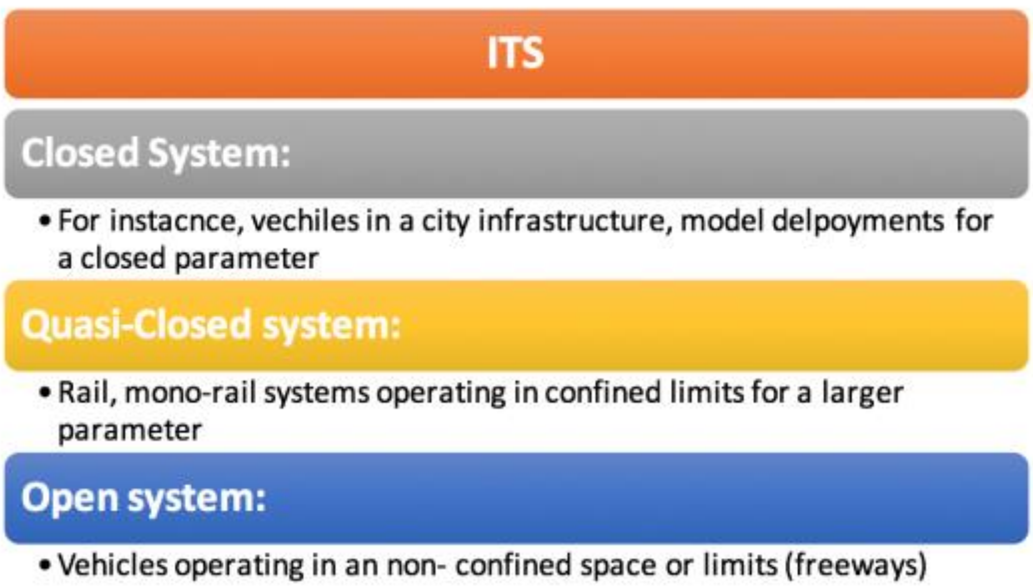

Figure 5.1(a) Types of ITS

Figure 5.1(a), shows a proposed category for ITS system. As stated in the figure above, these three types are clearly dependent on the safety application of ITS. These applications can vary depending on the conditions it is applied in. Consider a grid/network of the AV operating through the application of ACC and various other control laws. In order to admit the vehicle in this grid, it would have to pass through a similar toll both system where instead of toll it would consider the health of various components in the car. This information would help the subject to either pass or fail its admission into the grid. Based on the information gained from these sensor, the Health toll systems would make its decision based on the guidelines embedded in it.

The following figure 5.1(b), shows an example of the ITS HUMS application layout as a concept toll both health prediction system before advancing in the automated highway grid. It consists of an HUMS detector, which gains its information from through sensor beams from the on-board HUMS reporter (this reporter is a real-time monitoring device which has capabilities of conducting diagnostics and prognostics of the components). These are complex cyber physical systems which require a deeper understanding of the subject matter and will be covered in section 5.2

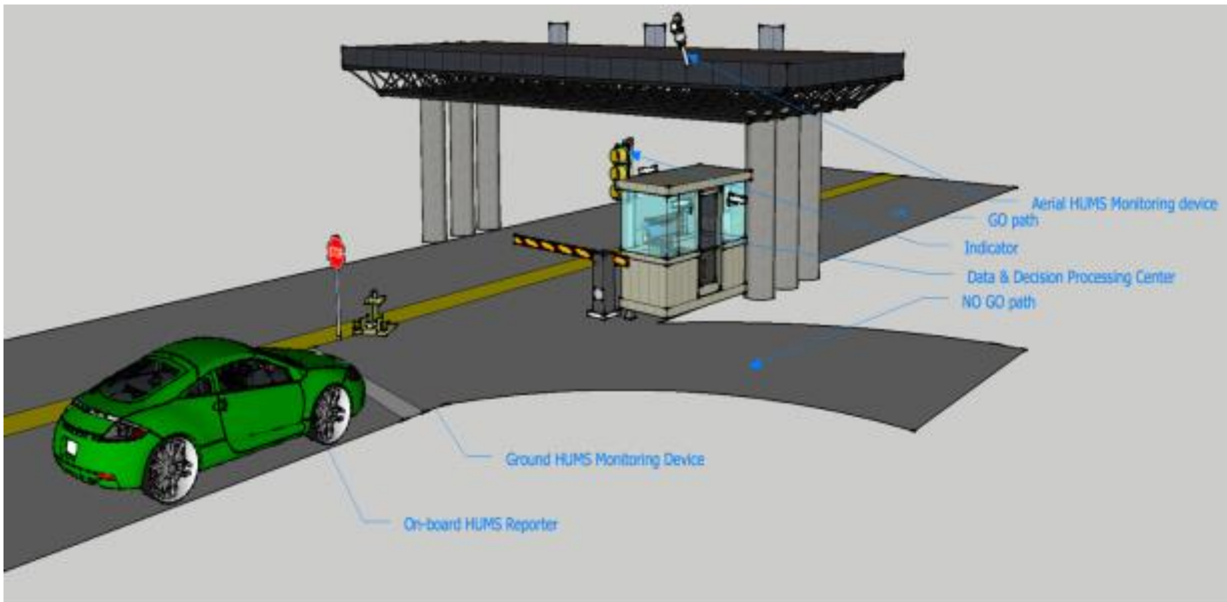

Figure 5.1(b)   HUMS Toll-Booth Concept

5.2 Cyber Physical Systems (CPS)

In order to have a better understanding of the term CPS, let us categorize it in three sections as seen in [40]:

i) What they are?

CPS can be considered as feedback systems, possibly with human in the loop. These feedback systems comprise of networked and/or distributed, adaptive and predictive, intelligent and real-time systems. Furthermore, networked and/or distributed systems consists of wireless sensing and actuation.

ii) What do they need?

CPS requires cyber-security, improved design tools that enable design methodology. Cyber Security can be broken down further into resilience, privacy, malicious attacks and lastly into intrusion detection. These topics are of high interests to the researchers in the field of Socio-Technical impact (which is covered in following section)

Design Methodology supports three things. First, specification, modeling and analysis of hybrid and heterogeneous models (models of computations, continuous and discrete), networking, interoperability, time synchronization. Second, scalability and complexity management through modularity and composability, synthesis and interfacing with legacy system. Finally, validation and verification on the basis of assurance, certification, simulation and stochastic models.

iii) Where can they be applied?

CPS has a wide variety of application in some of the sectors such as communication, consumer, energy, infrastructure, health care, manufacturing, military, robotics and transportation.

ITS concept falls under the Transport sector would be heavily relying on cyber-physical systems and its outcome. It is currently implemented as a model for test purposes in various cities by the NHTSA. It has been capitalizing on the emergence of information and communication technologies to efficiently manage the complex transportation network. ITS involves the application of these technologies to improve the performance of transportation systems and to increase the contribution of these systems to economic and social well-being. The three aspects as described in figure 5.2, can also be referred to as physical, cyber, and social, respectively. Thus, transportation-related research is inherently multi- and interdisciplinary in nature. A contemporary challenge to the ITS community is to integrate human knowledge and expertise with technical resources. ITS stakeholders are known to be working in isolated storage towers.

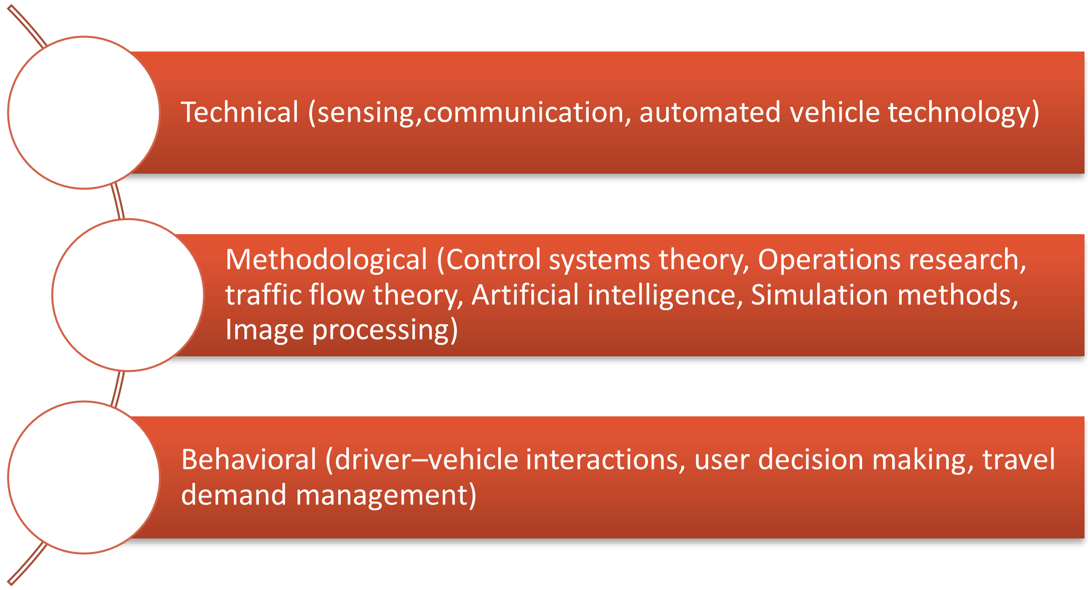

Figure 5.2 ITS Research focus area

5.3 Socio-technical impacts of AV's:

Systems that include technical systems, operational processes and also the people who use and interact with the technical system, can be known as socio-technical systems. It is in fact, a much more complex mixture. Figure 5.3 below shows the breakdown of socio-technical systems and its description.

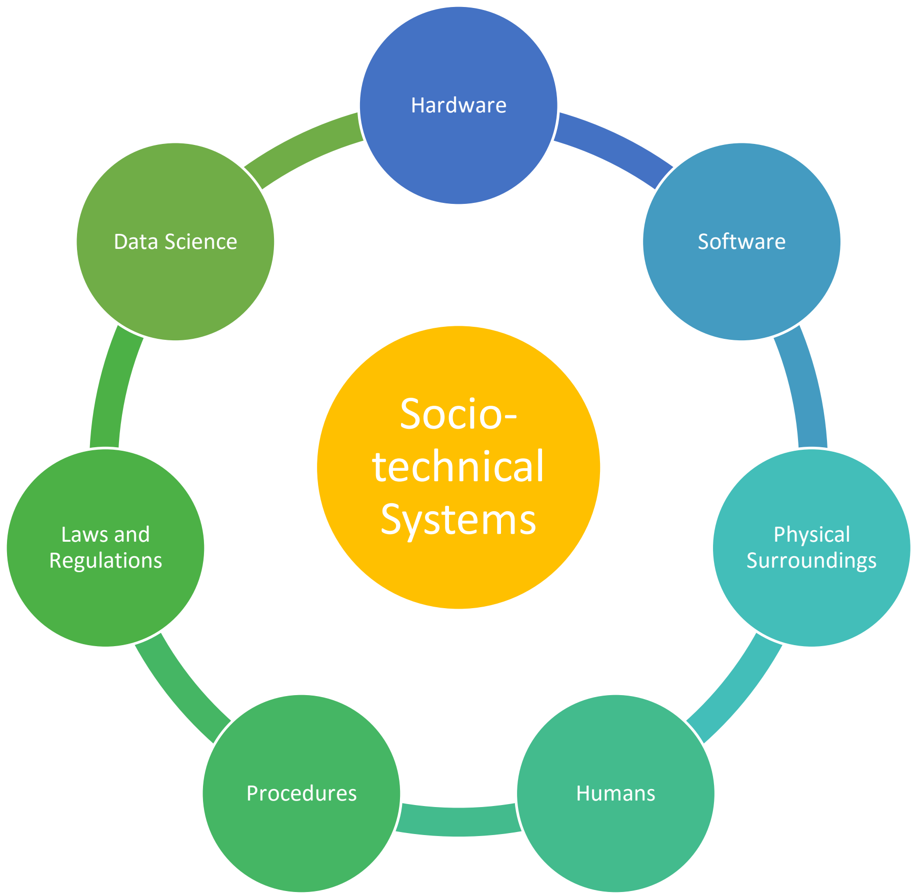

Figure 5.3 Socio-technical system classification

These seven factors stated above have been explained in detail in [37]. Autonomous driving has recently gained a lot of public interest with important implications for the scientific debate. Firstly, user-orientated perspectives play a crucial role in processes of sociotechnical change. Secondly, technology should be regarded in relation to the society where it is embedded [38] to create a more holistic picture of the possible impacts. Lastly, acceptance of autonomous driving is becoming a relevant topic on the research agenda [39]. Autonomous vehicles should not be understood as tools because they will be perceived as actors in a sociotechnical system. They are moving embodied agents that appear to behave intelligently. Humans have no experience regarding how to relate to AVs and how the AVs should relate to them. Hence, the understanding and applying the socio-technical models for day-to-day intelligently moving objects in essential.

5.4 History, Current State and Application:

The concept of intelligent transportation methodologies had been presented at the GM Pavilion of the 1939 World Fair in New York, which aroused a good deal of interest. In 1990's Automated Highway Systems (AHS) started receiving worldwide attention as a future transportation system. In the United States, the National AHS Consortium (NAHSC) was formed in 1994 to pursue the design and development of the AHS, aiming an AHS demonstration in San Diego in August 1997 and an AHS operational test in 2002. The primary purpose was to conduct research on transportation systems to find solutions for California transportation problems such as congestion, mobility and productivity of system, safety, air quality and environment, energy consumption, cost effectiveness and regional and statewide economic health [26].

According to the research conducted in [26], the architecture was divided into three important layers. The link layer: broadcast layer, it would share and access information from vehicles in the link for 1 or 2km stretch of highway. It would suggest changing the course of vehicles in a link based on accidents reported from downstream links, the coordination layer: as the name suggests it coordinated various movements performed by the vehicle in a link. For instance, platoon merge, platoon split and lane change, and the regulation layer: it consisted of control laws stated in a closed loop system for the vehicles to follow in longitudinal and lateral direction. Even though the framework presented itself as with viable option there were various technical challenges faced by the system. Communication, sensors and controls were some of the primary concerns for the process.

There has been significant increase in maturing ITS. There have been various model deployments conducted by the government. ITS has been the focal point of NHTSA and enough research has been conducted under their guidance and supervision by academia. Currently, there are test models deployed in Ann Harbor, MI., which according to NHTSA will soon be known as 'ITS hub city'.

5.5 Follow on

The HUMS application would be effective in a closed system as seen in figure 5.1(a) in comparison to quasi-closed/open system. In a closed system, V2V and V2I are being operated in a short range and small parameter (NHTSA Safety Pilot model). Failure of one component recorded by HUMS system would certainly help them gain the health of their system, but the prognostics delivered at the same time would not be as useful. Whereas in the case of quasi-closed and open system, these HUMS application would provide them with meaningful prognostics data for large parameter limits.

For instance, in an automated highway case, the vehicle would be operating in a full autonomous mode without or with minimal interference from the driver in unavoidable circumstances. There are two forms of HUMS that can be applied to gain meaning deductions about the systems health. First as seen in figure 5.1 (b), having a HUMS installed on the toll both to allow or reject the vehicle on the autonomous highway based on its health. Second, having a HUMS application running in the on-board systems of the vehicles while on the highway to create a V2V and V2I for safe operations.

Let us create a scenario in which a vehicle experiences loss of air in the tire and how the above mentioned two forms would perform in this situation. In the first form, at the HUMS toll-booth concept, the on-board HUMS would interact with the external HUMS device to process the health information and prognostics of that tire. This in return would either accept or reject the vehicle based on the prognostics received on the tire (i.e. prognostic would determine whether the tire would be safe to operate on the specified route by the driver without creating any disruption in the fully autonomous highway) from the booth. In the second form, if the tire is faced with loss of air after passing the toll both, the V2I would come into play where the central network would guide the vehicle out from the autonomous mode.

Chapter 6. Conclusion

In conclusion, there are few significant criteria's and requirements for autonomous vehicle that should be implemented for these vehicles to operate safely in ITS according to my analysis. The following are listed as follows: Electric power steering system, Adaptive cruise control or System which allows electronic control to brake and gas pedal.

Autonomous vehicle is not only limited to electric vehicle, but also is applicable to modern petrol-powered car as well, as long as the cars feature the mentioned technology. Since electric cars already contain those features in an easy to integrate form, which makes them ideal candidate for autonomous vehicle for ease of use and cost.

Due to the mentioned requirements, the components in charge of those systems are actually the new critical components. Sure, for a petrol/combustion engine car, the engine, transmission and brake system (all mechanical) are still crucial, but in the essence of autonomous vehicle, they are not.

HUMS system must be able to monitor and analyze the data of these components, along with sensors monitoring the performance of these systems.

The fundamental technology behind autonomous vehicle can be roughly broken down into two main ones: an effective Adaptive Cruise Control system (ACC), and a responsive Electric Power Steering system (EPS). Without these two systems, a car cannot be controlled electronically, hence, it would never be an autonomous vehicle. Therefore, it is reasonable to categorize these two systems and their parts as critical components of an autonomous vehicle. Undoubtedly, there are various other factors to be considered in the development of a complete autonomous vehicle, such as, its sensors systems that provide information of the operating environment, or car-to-car communication, or machine learning and computer vision.

Theoretically speaking, it is reasonable to say that as long as good ACC and EPS systems are available, any car, electric, hybrid or purely combustion-based, could be made autonomous by pairing those systems with a computerized control center and a systems of sensors. Therefore, the electro-mechanical ACC and EPS systems could be considered critical components in an autonomous vehicle, and they are targets to implement the Health and Usage Monitoring System on. Interestingly, at the moment, the leading semi-autonomous or autonomous vehicles run on electric motor instead of the conventional engine. This trend suggests a future in which electric cars will dominate the market and completely overshadow combustion engine cars. Nevertheless, the rise of electric car is still in its infantile stage; therefore, the implementation of HUMS to autonomous vehicle still has to consider both electric and combustion vehicle.

Originally, HUMS was created to actively monitor and analyze the condition of mechanical parts in aircraft, specifically helicopter [30]. The core principles of HUMS allow us to monitor the condition of the engine, transmission and suspension of the combustion-engine autonomous vehicles, just like how HUMS can be applied to a conventional automobile. Data from HUMS in general depends on the component it is monitoring. For shaft, HUMS would collect rotational speed and angle; for the engine, HUMS utilizes engine sensors to monitor air/fuel ratio, spark fire timing, internal pressure, output, etc. [30]. The monitored parameters might be different, but the form of data in HUMS is quite consistent. Information from sensors are recorded dynamically in real time in various frequencies, depending on component parameters and design, and are stored onboard or transmitted to a database. The data usually contains the values of the parameters collected by the sensors, and their specific time. HUMS data is then investigated onboard or at the database, either by computer or a trained operator [30]. Core analyses would be data trend fitting and finding, and comparison between the interested vehicle and other similar ones. Results from the analyses would help identify problems within the autonomous vehicle, setting up its maintenance schedule and evaluating the performance which also would help improving the design.

Regarding electric autonomous vehicles: they often are consisted of much less components compared to the combustion-engine vehicle. Similar to most current electric cars, electric autonomous vehicles power come from sets of Lithium Ion batteries mounted in the floor of the vehicle, or in the back. The DC electric power is transferred to a control unit, which is capable of several things: converting DC to AC to drive the electric motor, taking in data from environmental/safety sensors to send out command to ACC and EPS systems, managing the active suspension system, and much more. The other important part of an electric vehicle would be the electric motor(s). Typically, electric motors can have a higher power-to-weight ratio (Nissan GTR

R-35 3.6L V6 Turbo Power-to-Weight = 228W/kg; Tesla Model S Electric Motor = 362hp/70lb ~ 8500 W/kg) than traditional combustion-engine [31] [32]. This allows autonomous electric vehicle to mount multiple electric motors to accomplish a truly differential power train without being too dependent on a transmission system. For electric vehicles, the types of electric motor and their configurations determine the necessity and the function of mechanical transmission system. Most of the time, only single-speed gear boxes are installed on autonomous electric vehicle, and usually only for efficiency purposes. The total omission, or lesser complexity of transmission in autonomous electric vehicle actually boost the reliability of the vehicle as less mechanical parts are involved in the operation of the car.

The graduation from mechanically-centered structure of autonomous electric vehicle diminish the importance and effectiveness of the original HUMS, which primarily is a monitoring system and principle for mechanical parts (gears, shafts, springs, etc.) of air craft. Nevertheless, the approaches of HUMS are still useful, and personally, I think that it could still be applied to autonomous electric vehicle with slight alteration.

So how HUMS integrate electronic components and electrical systems (especially the EPS and ACC systems)? First and foremost, autonomous vehicles systems rely on input from environmental sensors and pre-determined rules and parameters. Additionally, besides providing information about the surrounding of the vehicles, sensors also play a huge role in optimizing and ensuring the performance of the vehicle. Therefore, given the importance of sensor in autonomous and automotive technologies, the health of sensors used in autonomous vehicles must be reflected in HUMS. Even though most control systems in autonomous vehicle contain functions to verify the integrity of specific sensors, sometimes, the report might lag, be lost in noise filtering, or be too generic. The dynamic and robust characteristics of HUMS help address these problems and augment the user and operator knowledge regarding the performance and health of the many sensors in an autonomous vehicle. Dedicated instrumentation amplifier (INA) could be installed onboard, or at the database to effectively extract even the smallest deviation in the sensor performance without having to directly alter the control scheme of the autonomous vehicle [33]. The data flow from the sensors could also be used to validate the condition of the sensors by following NASA's Bayesian Network method in validating aerospace vehicle's sensor from their data [34]. Furthermore, a consequence of HUMS would be the formulation of a network of similar vehicles. The network could then be extended into a network of sensors, and their performance could potentially be linked and compared to each other using extensive software and algorithm [35]. By setting up references and candidates for comparison, the health of the sensors of a specific vehicle can be easily estimated and analyzed at any given time.

Besides caring for the health of the sensors in autonomous vehicle, HUMS could potentially be extended to accommodate the monitoring and analyzing of electric signal input and output of the autonomous vehicle controller/ECU/Mainboard. Modern controllers, including those used in the various systems of autonomous vehicles, nowadays are built on PCB. Usually, to assist in debugging and analyzing the highly complicated PCB system, test probes are introduced in strategic points. Perhaps, the HUMS could interact and extract information from these test probes as well, and analyze the electric signal in and out of the PCB. With enough modelling and information from manufacturer, user could easily analyze the electric signals to gauge the performance of the autonomous vehicles and seeing which parts are not operating as intended, without having to disassemble the vehicle. Additionally, HUMS's ability to transmit raw data to be analyzed in a remote location also allows to utilize and setup intensive and powerful analytic equipment to successfully evaluate the data without burdening the vehicle too much.

There are two major approaches to the integration of HUMS into autonomous vehicle. Figure 6.1 illustrates the series approach, in which HUMS processor extract information from the various dedicated ECUs of the autonomous vehicles. In other words, the output of the ECUs serves as inputs for HUMS. Figure 6.2 demonstrates another potential approach in integrating HUMS into autonomous vehicle. In this approach, HUMS directly interact and communicate with the various sensors within the vehicle (probably via CAN communication bus). Implementation of the first approach, the series block diagram, is generally simpler. In this approach, since HUMS extract information through the ECUs instead of the sensors, changes to the infrastructure of the vehicle would be minimum. This also means that by following this approach, even current conventional automobile and semi-autonomous car could implement HUMS with relatively few adjustments and accessories, and with ease. The major drawback of this approach is the same as with any other series system: the function and reliability of HUMS depend on the performance and reliability of the prior elements (the ECUs, the sensors, etc.) – if something else fails, HUMS would probably not work at all. Additionally, if data is throttled, heavily or incorrectly filtered in the previous processes, then HUMS would receive data that does not necessarily reflect the true conditions of the component. The second approach – the parallel connection, alleviates the dependence of HUMS onto the other systems in the autonomous vehicle. It also allows HUMS to directly collect raw information from sensors without unnecessary filtering from the other process. However, this approach requires additional time and resource, and perhaps, a complete overhaul of the autonomous vehicle design, to fully integrate HUMS with critical systems' elements in the autonomous vehicle. Regardless of the approaches, it is important to try to make HUMS as modularized as possible to ease the data analyses processes, and to isolate the monitoring aspect of the system while still maintaining a comprehensive evaluation of the vehicles.

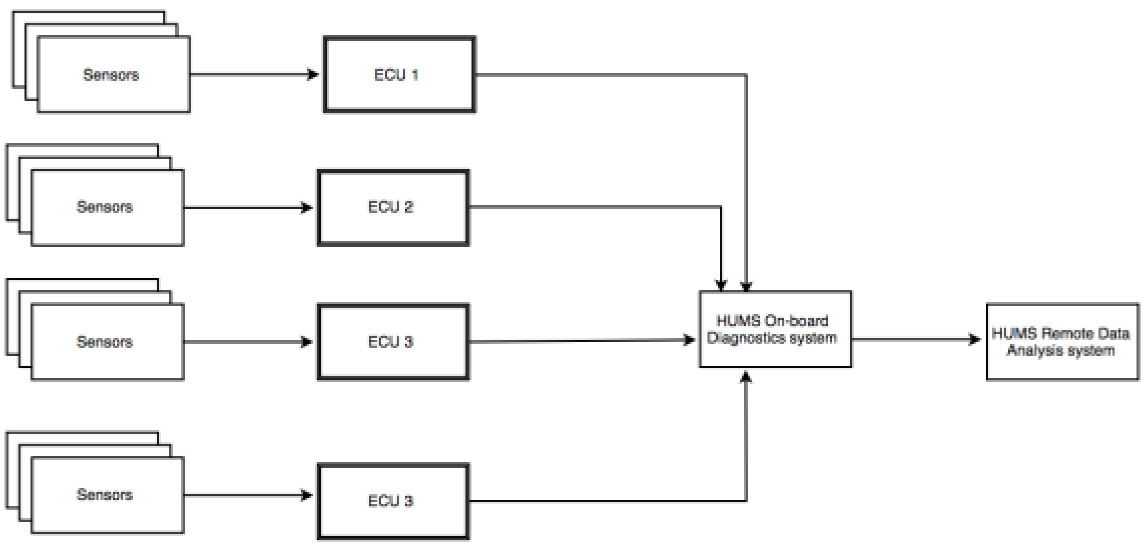

Figure 6.1 Series flowchart for framework for HUMS and sensors

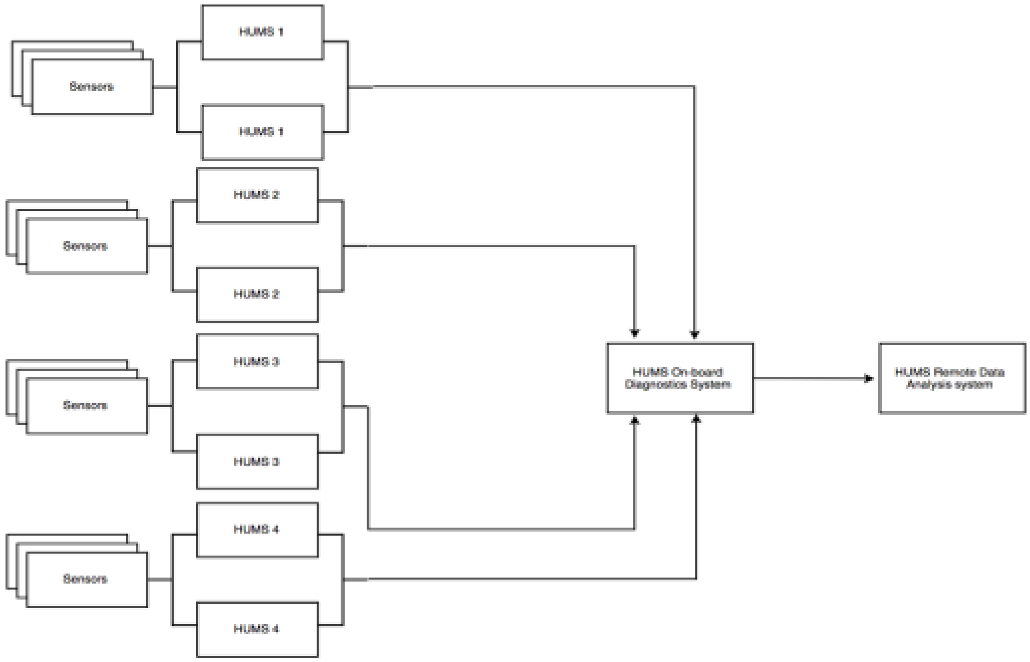

Figure 6.2 Parallel flowchart for framework for HUMS and sensors

HUMS's ability to transmit raw data to be analyzed in a remote location provide the opportunity to setup intensive, dedicated and powerful analytic equipment to successfully evaluate the data without burdening onboard computer. Data from autonomous vehicles would most likely be analogous to the data from existing HUMS that is used on aircraft. This means that the data acquisition and analyzing techniques of aircraft HUMS could be more or less directly transfer and applied to autonomous vehicle. Reliability analyses, descriptive and predictive statistical analyses could be carried out to predict the remain-useful-life of the autonomous vehicle's components, and its entire system as a whole. The results of the analyses will stimulate and help formulate condition-based maintenance for the autonomous vehicle. Furthermore, integrating HUMS into autonomous vehicle – an entirely new platform, opens the opportunity to test and include the latest HUMS findings that require major changes to HUMS.

Hypotheses:

H1: A HUMS application for autonomous systems would prove improved safety as reliability over existing methods.

H2: Initial screening of an AV prior to entrance on to an ITS would improve the performance of the ITS.

Future Steps:

To successfully create a functioning HUMS system of an autonomous vehicle, much more work is needed. As mentioned earlier, FMEA, FMECA and FTA will need to be carried out for each autonomous vehicle model, and for the generic automated automobile as well, in order to pin-point the components and elements in a vehicle that require HUMS application. Following that, descriptive and precise mathematical models are capable of representing the founded failure mode and mechanism will need to be developed to accurately interpret inputs from the systems of sensors in the autonomous vehicles. Even more mathematical models will need to be developed and tested for analyzing the data from HUMS and deriving practical insights to help predict the behavior of the components and set up maintenance plans. Intensive testing of prototype would also need to be performed to verify the practicality and benefits of autonomous vehicle HUMS. Furthermore, infrastructure supporting HUMS would need to be designed and built, and professional personnel specialized in working with autonomous vehicles HUMS would need to be trained and practiced. There is still much work to be done to integrate HUMS into autonomous vehicle. Yet, the great benefits of HUMS in aircraft have been observed and proved over time; and there is no reason why the autonomous vehicle industry could not inherit those benefits. Implementing a HUMS into an autonomous vehicle would greatly improve the vehicle reliability, safety, availability and performance, and streamline the vehicle's maintenance processes, hence, greatly saving time and cost in ensuring the car is in working condition

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