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Real-Time Sensor Data Development for Smart Truck Drivetrains

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Real-Time Sensor Data Development for Smart Truck Drivetrains

by

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THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE IN ENGINEERING

THE UNIVERSITY OF TEXAS AT AUSTIN

December 2017

Acknowledgments

I greatly appreciative Professor Del Tesar for such great opportunities and guidance. This work would not be possible without the great care of my family. A special thanks to Dr. Laurens Van Eykeren for reviewing my initial efforts and to Dr. Richard Crawford for a final review. I appreciate all the work Betty Wilson does for the Robotics Research Group.

Real-Time Sensor Data Development for Smart Truck Drivetrains

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The University of Texas at Austin, 2017

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Heavy articulated transport vehicles have a poor reputation associated with dramatic road accidents with frequent fatalities for those in automobiles. The result of this work is a formal data flow structure to enhance real-time decision-making in complex mechanical systems to increase performance capability and responsiveness to human commands. This structure recognizes the multiple layers of highly non-linear mechanical components (actuators, wheel tire & ground surfaces, controllers, power supplies, human/machine interfaces, etc.) that must operate in unison (i.e., reduce conflicts) in real-time (in milli-seconds) to enhance operator (driver) control to maximize human choice. This work contains a discussion on dependable sensor data is vital in complex systems that rely on a suite of sensors for both control as well as condition monitoring purposes as

well as discussion on real-time energy distribution analysis in high momentum mechanical systems. The focus will be on tractor trucks of class 7 & 8 that are outfitted with an array of low-cost redundant sensors leveraging advances in intelligent robotic systems.

This work details many topics including:

- **Most relevant sensor types and their technologies,**
- **Designing, implementing, and maintaining a multi-sensor system using feasible industry standards,**
- **Sensor signal integrity and data flow processing for decision making,**
- **Asynchronous data flow methods for operating decision making schemes in real-time,**
- **Multiple applications to enhance tractor trucks systems with multi-sensor systems for real-time decision making.**

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Chapter 1

Introduction

Heavy articulated transport vehicles have a poor reputation associated with dramatic road accidents with frequent fatalities for those in automobiles. These vehicles (class 3-8) represent 60% of the freight in the U.S. as part of a $1 trillion per year economic activity labeled land transport. The federal government is funding research grants (DOE, DOT) associated with autonomy and fuel efficiency. Both are helpful. However, without a similar emphasis to make the trucks smarter, much of that investment will have very little impact. For example, articulated trucks frequently jackknife when in poor weather (low surface friction) especially when lightly loaded with almost no warning to the driver. Further, rollovers are about 50% of truck accidents caused by wind, poor traction, emergency maneuvers or rapid lane changes. The published literature clearly describes all these conditions with elegant mathematical simulations and architectural concepts to control trailer roll, fifth wheel rotation, or lateral trailer acceleration. Only one paper properly describes the need for articulated responsive steering of the trailer axles by using hydraulic actuators which are notorious for being sluggish,

fail unexpectedly, require excessive maintenance, and are difficult to make fault tolerant ((Tesar, 2016*c*)).

This report deals primarily with the acquisition and management of real-time sensor data from heavily loaded cross country transport vehicles (semi-trailer trucks). An extensive literature survey was performed by D. Tesar in *Technical Description of A Smart Truck* in 2016. This survey yields many conclusion and recommendations, which are necessarily excerpted here to make this report more complete as to its relevance to the land transport industry. These excerpts can be found in chapters 1 and 2.

This work contains the framework to argue for why modern intelligence-based decision making is now possible for moving tractor truck management and is a critical step in modernizing this type of transportation. Due to ever lowering costs in sensor technology, the real-time operation of tractor trucks can be monitored using a varied and low cost sensor suite to characterize a wide range of physical phenomena (vibrations, bearing temperature, truck/trailer oscillations, noise, cargo parameters, door/hatch positions, etc.) to provide local and system wide awareness of key conditions influencing timelines, efficiency, potential for bearing failures, road crash, and overall safety and to transmit this awareness to necessary human operators and decision makers using prioritized criteria and visual operational performance maps. All of this must be done in

real-time (1 to 10 m-sec.) to allow for decision development and actuation response to rapidly enhance system performance.

This framework uses decision structures that use updated data from sensor fusion, process awareness (performance maps based decisions for enhanced efficiency, speed, braking, needed repairs or remaining useful life, human oversight, human-system interface, etc.) to constantly enhance performance and as a consequence combine Sensor/Process/Fault (SPF) decisions in a new level of truck effectiveness, security, availability, and safety. Elements of such a system are:

Energy harvester	SPF for truck components
Sensor suite	Truck CBM
LAN and truck CPU	Truck system criteria
Sensor data management software	Operator criteria
Truck operating software	Truck/Network operating decisions

1.1 Revolution in Efficient Commercial Transportation Vehicles

The dominate idea recently developing to greatly increase system performance in commercial transport vehicles is to actively manage in real-time all unwanted system energy such as inertia, spring, tire, trailer swing, etc., by using responsive actuators to actively remove such oscillating stored energy before larger oscillations results. Large oscillations tend to develop into common tractor truck failures such as rollover and jackknifing, which cause tremendous damage and delays. To prevent such disasters, incipient oscillations must be measured and cancelled in real-time (near 10 m-sec.) and it is proposed in this work to develop and demonstrate a number of intelligent trailer options as the basis for a new class of versatile smart trucks.

The primary source of feedback for these responsive actuators will be a redundant network of low-cost sensors measuring all necessary physical aspects of a target vehicle. Of primary interest is the wheel-ground surface interaction where traction results in a linear force driving the connected vehicle body. Traction, a highly nonlinear phenomena, is the only active control for a vehicle driver and should be a high priority when dealing with vehicle control.

However much of U.S. technical development in vehicles is extensively concentrated on the front end power generation segment of the more-electric vehicle (tuned engine/generator, batteries, super cap, etc.) with limited development of the back end power utilization segment (powered drive wheels, active suspension and camber, etc.). While traction is a highly nonlinear component that can change rapidly over time, minimal attempts have been made to improve capability in this aspect of real-time vehicle control.

Further justifying the need for data development are the proposals for added actuation to tractor trucks and the expected actuation enhancements. Such developments are now feasible and will require a developed information flow for feedback in order to operate at full potential.

The feedback will occur by means of high performance, cost effective actuators to enhance command control primarily of the truck trailer by means of improved braking, steering, suspensions, and coupling among serial trailer modules. Further, as stressed in this document, fault tolerance in data handling and command signals must be matched by fault tolerance in the control system and the actuators in the multi-input, multi-output system with ever increasing complexity and lower cost.

1.2 Intelligent Systems

Vehicles are complex systems under human command. Whether for light (automobiles) or heavy (commercial) systems, there is a constant need to enhance performance (fuel efficiency, safety, responsiveness, cost, availability, etc.) and to increase effective interaction between machine and operator. To improve performance, sensors must become more intelligent – distributed in function and in location – to enable a decision structure to provide more operating choices (or recommended options) to effectively respond to operator command(s) (for example operation in poor weather or heavy traffic), to prevent failure (no single point failures and safely

escaping dangerous scenarios/conditions), and to enhance efficiency (combined power sources in hybrids and reduce mundane operator tasks to minimize fatigue). Operational choices can be useful only if real-time awareness of the benefits of a selected set of choices meets performance objectives under a given set of conditions. This real-time situational awareness can only be assessed by accurate data on all component and system conditions, which means a widely distributed set of sensors, generating useful data in real-time. To justify outfitting large systems with various sensors, each sensor module must be low cost and effective, including minimal maintenance.

The majority of work on vehicle sensor development has concentrated on performance and safety in terms of internal devices to measure physical phenomena such as velocity, acceleration, vibration, noise, temperature, kinetic energy measures, roll/inclination, braking/throttle, torque, etc. D. Tesar has a liturature survey of sensor for possible use in tractor trucks in *Development of Internal Vehicle Sensors* in 2016. These internal sensors provide assistance to the driver in decision making, enable prediction of component failures (condition based maintenance), and data archiving for off-line analysis with the goal to improve component design and better/more efficient route planning. Recent vehicle sensor developments have concentrated on external devices to support autonomy (driverless cars) and connectivity (inter-vehicle communication in heavy traf-

fic). This move towards autonomy demands exceptional precision (sensor accuracy and signal quality). Unfortunately the sensors of today do not provide this level of exceptionalism at a near real-time frequency (refresh rate). This weakness will be difficult to eliminate, as demonstrated by the recent accident by a Tesla car where the autonomous vehicle crashed and killed the passenger due to a computer vision failure.

Clearly, the need for intelligent vehicles is a broad array of internal sensors to manage all the physical choices the operator or customer wants or needs, especially in heavy transport vehicles where high momentum occurs with greater value in goods at risk. Heavy land transport vehicles carry 60% of the freight in the U.S. These are mostly diesel powered semi-trailer trucks which have a good accident record. However the economic and human cost is high when they are involved in a crash. The ultimate goal of this work is to reduce driver cost and increase payload while improving safety. This, then, suggests the use of road trains (3 to 5 modules) as done in Australia. This requires a central power source at the tractor with distributed power to each module, which can only be done with full intelligence at each module. Safety implies full awareness of the kinetic motion of each module and the effective traction control of energy oscillations or sudden roll effects from wind. This entire forecast becomes feasible only with real-time data collection for complete situational awareness of each train module and components in real-time.

Some outstanding vehicle sensor development has occurred by Rockwell (self-organizing wireless networks) and by Honeywell (specific transducer classes). This review does show that sufficient data quality and cost are continuing issues to improve. The data needs to be available in 1 m-sec. from lower power demand modules (to preserve on-board battery energy). It now appears necessary that node standardization be pursued by the vehicle industry to further enhance performance/cost ratios, with increasing emphasis on reliability. Some sensor suppliers are integrating several transducers into a single node (gyro, acceleration, inclinometer, as the basis for a kinetic node) to further reduce network complexity, cost, and maintenance. Networking that is continuously configuration-managed to maximize data fusion and to avoid single points of failure requires sophisticated and ever-evolving algorithms. It now appears necessary to develop a manual battery recharging system to enable long-duration operation of these internal sensor networks. Finally, network security should be considered to ensure the safety of the vehicle and the collected data to prevent unwanted intervention by third parties.

Intelligence implies three major technical activities:

- Real-time data acquisition,

- **Data reduction leading to command decisions,**
- **Action response using distributed actuators.**

To summarize, developing intelligence in machines is emerging to principally impact the technology spectrum associated with satisfying human needs and human commands in real-time.

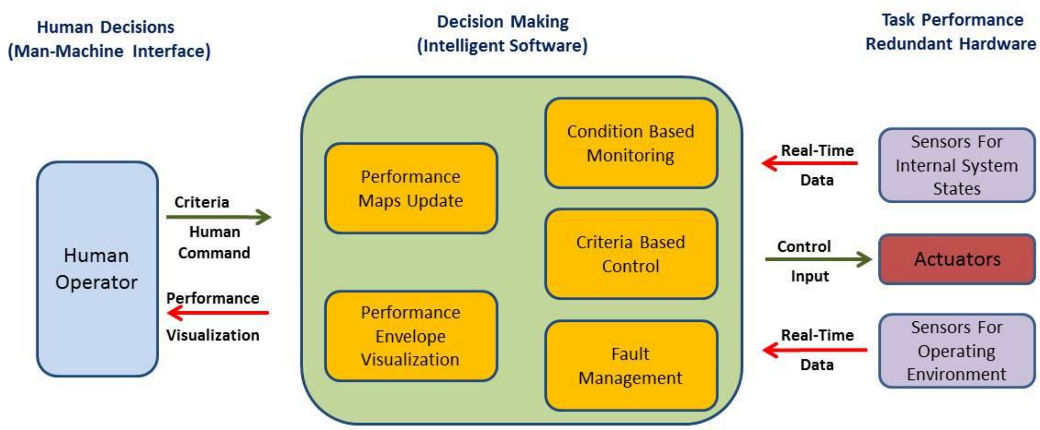

Figure 1.1: Overview of intelligent systems

1.3 Intelligent Decision Making in Real-Time

The difference between risk and uncertainty is the knowledge of the associated probability of an unknown outcome. Uncertainty is the absence of a known probability distribution of outcomes. Understanding the amount and quality of object features in an operation environment reduces the uncertainty in a robotic system and improves clarity in system risk or predictable failure. Such clarity

provides a framework for anticipating the impact for new tasks and operation protocols.

The underlying focus of this work is to design systems away from uncertainty towards allowable risk management. This work is an in-depth science work for developing real-time intelligent decision making in tractor truck systems using common low-cost sensors and structured data flow and control tasks. The framework developed in this work would minimize uncertainty in complex operations - complicated (multiple dimensions or degrees of freedom) and adapting (changing over time or not time-invariant) - throughout truck operation and provide a framework for implementing new tasks or operation protocol more effectively. Such an intelligent system will allow an operator to be free of dangerous environments and of mundane tasks, enabling the operator to perform duties at an enhanced capability. This will be done by adding more automation and decision making to the system, in real-time, adding more operational capability to the system compared to a pure teleoperation, which is costly in operator time.

Sensor fusion is a intelligent combination of mathematics and the interpretation of the physical meaning from multiple signal sources so that the target information can be resolved/merged into useful information to enhance system and sub-system performance (Krishnamoorthy, 2010). Each signal must be properly scaled, filtered, and interpreted. Combinations of signals must be created to indicate overall resource management (losses, efficiency, acceleration, torque level, lost motion, stiffness, etc.). All the information is used to inform the local status of components or the overall system as it moves along embedded performance maps/envelopes that describe performance. Having 10(+) distinct measurands creates a level of robustness to ensure reliable decision information. Useful questions for multi-sensor system design to enhance operational decisions and performance include: how volatile are the performance maps, what norms best describe their physical meaning, how accurate is the measured data, what update rates are necessary, etc.

In the case of a sensor fault – no signal generation or unreliable/noisy signals – the remainder of the sensor network will be used to infer lost data. This capability will derive from the performance envelopes which are generated in various combinations of the component performance maps, all using distinct sensor signal sources. A strategy can also be developed for sensor maintenance as a component of Condition Based Maintenance (CBM).

Developing embedded software is essential to provide functionality like communication, data processing, and implementation of various features that collectively contribute to intelligence, namely, criteria-based decision-making algorithms, Condition-Based Maintenance (CBM) routines, etc. Information from sensors has to be

analyzed, interpreted and manipulated systematically in software in real-time or 1 to 10 m-sec. to produce information of value to the higher levels of the control hierarchy. This includes control modules that support error-handling, mathematical functions, storage of system/actuator-related data, abstraction of input-output devices, inter-process and network communications, algorithms for sensor data validation and fusion, CBM, fault tolerance, performance envelope generation, criteria fusion, etc., which are used in decision making processes. Higher level system commands are then processed; along with a combination of the stored performance maps and envelopes, the measured sensor reference, parametric models and user-specified criteria, to yield appropriate control signals for operation.

Autonomy is always a popular desired goal of control and decision making. To no surprise, autonomy is being considered for cross-country tractor truck operation to reduce the cost of operation (less dependence on on-board drivers), improved safety (more rapid and accurate response to unsafe conditions) and improved fuel efficiency (better balanced wheel traction control). In most trucking operations today, the two largest cost elements are labor (largely the driver) and fuel. A distributed intelligent system enhances these features by enhancing engine operation, control of each wheel's torque/traction for safety and fuel conservation and also for

accurate (m-sec.) responses to rapidly changing road conditions, if such systems were in place.

Present truck tractors require 100% of the truck driver's attention for their on-road operation. This is an expense that has been a high burden for truck transport. Further, railroad freight trains will also go through a revolution for cost effectiveness, timely delivery, and safety. To remain competitive, the truck industry must not only reduce expenses, it must also improve its level of safety to maintain the public's acceptance of its use of the national highways. Autonomy is not going to be a simplistic superposition of sensor-based decision making to replace human operator decisions. Autonomy has a greater productivity potential if the truck tractor (and also the trailer) is made responsive to much higher levels of command. Doing so will create an enhancing technology that provides decision making, sensors for real-time operational data, distributed choices throughout the truck system, and no single point failures, all combined for a revolution in truck tractors.

1.4 Multi-Sensor Approach

Using multiple means to collect desired data is a crucial aspect to consider when designing a system for intelligent control in real-time using multi-criteria decision making. Mechanical systems are getting more complex to respond to human demands of increasing output functionalities and increasing performance. Non-linearity in a system will provide for complex and changing output functions (a multi-input multi-output system), but classical control methods cannot manage this complexity and deal with the inherent uncertainty in the system's operation. A system equipped with multiple sensors will provide better awareness about its state and the operating conditions reducing uncertainty and guesswork from the system control. Then there is a question about uncertainty in the data provided by these sensors but sensor data uncertainty can be reduced in a multi-sensor environment using sensor fusion techniques and fault tolerance. A multi-sensor system will enable intelligent control in real-time to extract the best possible performance from the system to match ever changing objectives.

1.5 Design Philosophy for Smart Trucks

This selection of actuator based solutions for smart trucks is remarkably different from that represented by Nikola Motor Company, a hybrid tractor truck design company, or that funded by U.S. federal agencies, such as DOT, DOE and DARPA, yet it represents a means to dramatically and cost-effectively improve safety, enhance driver decisions, reduce fuel consumption and enhance payloads.

This work leverages the ***Next Wave of Technology*** (Tesar, 2016*b*) technology base to modernize transportation systems (freight trains, cross-country trucks, urban fleet vehicles, buses, and container transporters) to maximize their availability (no single (point failures), their fuel efficiency (to meet 2025 U.S. fuel standards), their open architecture (plug-and-play for rapid repair and refreshment) and reduced life cycle cost (OEM control of a competitive supply chain for assembly, updating by the customer, and repair).

Most transport vehicles have a closed and passive architecture, which is designed and assembled as one-off systems whose outdated components represent single point failures and virtually no active response to command. Generally, these systems have a decision latency of 1 to 2 seconds which represents a travel distance of 100 to 200 ft, at 70 mph. This latency diminishes the potential benefits of autonomy and active response to bad weather (road conditions), traffic conditions (safety) or GPS-based embedded road plans (curves, hills, speed limits, etc.) (Tesar, 2015).

These transport systems are all wheeled to maximize dexterity and reduce rolling friction on presumed well-maintained road surfaces. Their travel routes today can be planned (embedded motion parameters) for maximum safety, efficiency, timeliness, etc., with differences of the actual travel (weather, traffic, wheel contact uncertainty traction, etc.) as the basis for uncertainty/differences to govern real-time decision making under the command judgment of the operator (who sets priorities, criteria, and visually interprets good/poor operation). In every case, sensors inform the decision process, actuators respond to command, the operator judges the overall response, and predictive analytics evaluates archived performance data to improve route planning and structure system component design and operational criteria. Figure 1.2 illustrates the overall Smart Truck system.

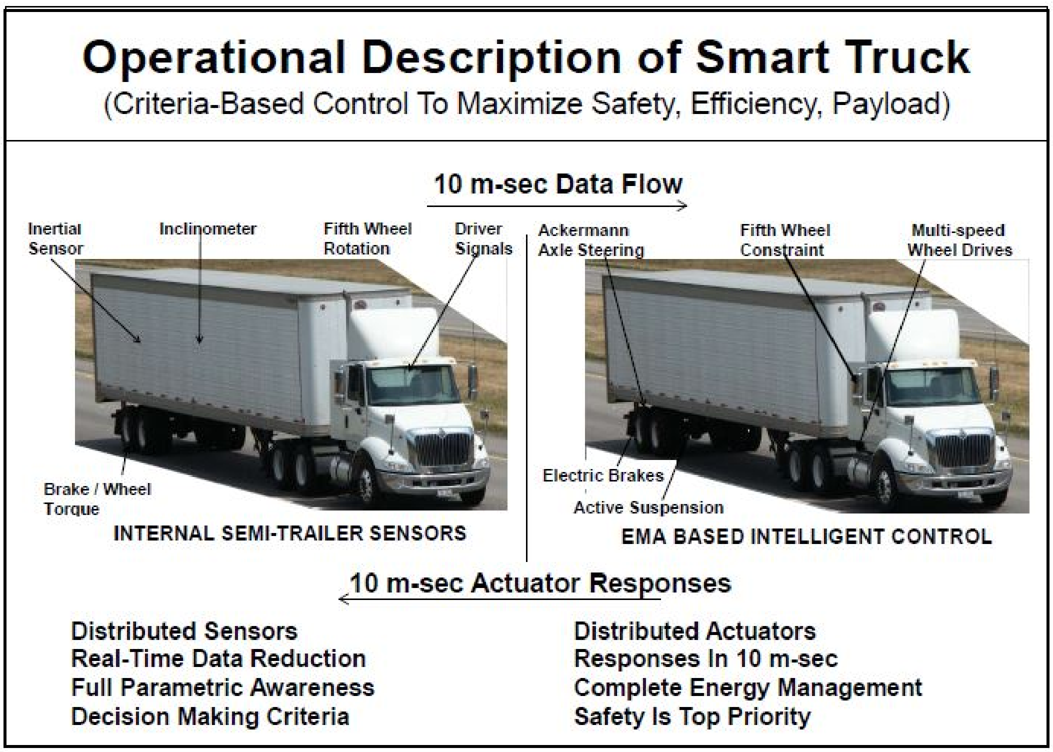

Figure 1.2: Prescribed intelligent system for tractor trucks.

Chapter 2

Brief Tractor-Truck Crash Dynamics

This chapter contains a brief overview of tractor truck dynamics with a focus on common crash scenarios and develop the parameter framework for developing sensor synthesis and data flow control. The purpose of this chapter is not to replace leading literature on tractor truck dynamics, such as dated but well cited sources (Dorion, Pickard and Vespa, 1989; Liu, Rakheja and Ahmed, 1997; Winkler and Ervin, 1999) but to provide a relevant dynamics background for the scope of this work.

2.1 Shortcomings in Current Truck Operations

Current tractor truck vehicles have many obvious mechanical issues at high speed operation, namely: high load mass,high center of mass, high air drag (exposure to wind disturbance), long body, and typically passive trailer (lagging vehicle bodies). Mass issues get worse when loaded, which is the primary function of the transport vehicle.

Total Number of Class 7 and Above Fatal Truck Crashes by Year			
Year	2012	2013	2014
Number of Fatalities	3,136	3,250	3,190
Class 7 and Above Truck Crash Statistic for 2014			
	Number of Fatal Crashes in 2014	Injury Crashes in 2014 (MCMIS Data)	Towaway Crashes in 2014 (MCMIS Data)
Number of People Involved	3,190	40,753	71,939

Table 2.1: Crash statistics vehicle class 7-8

2.1.1 Crash Statistics

Due to their massive sizes and heavy weights, trucks can cause serious damage and death, should they be involved in an accident. To inform the public about traffic safety and to bring the dangers of truck collisions to light, various agencies throughout the U.S. – including the U.S. Department of Transportation (USDOT), the National Center for Statistics and Analysis (NCSA) and the National Highway Traffic Safety Administration (NHTSA) – have compiled the following statistics regarding the incidence of different types of truck accidents in the U.S.

Information from NHTSA in Table 2.1 indicates that in 2014 over three thousand people were killed in tractor truck crashes and over seventy thousand incidents involved a towaway, which nearly always involve significant vehicle damage (usually multiple vehicles) and significant time disruptions.

2.1.2 Rollover Case

Many factors related to heavy vehicle operation, as well as factors related to roadway design and road surface properties, can cause heavy vehicles to become yaw unstable resulting in a roll. (Liu, Rakheja and Ahmed, 1997) indicates that rollovers are due to excess lateral accelerations storing potential energy in the suspension springs and exceeding lateral tire sliding forces; and, this can occur without the driver's knowledge (the driver's reaction time is too long). Listed below are several real-world situations where stability control systems may prevent or lessen the severity of such crashes.

- Speed too high to handle a curve — The entry speed of vehicle is too high to safely negotiate a curve. When the lateral acceleration of a vehicle during a steering maneuver exceeds the vehicle's roll or yaw stability threshold, a rollover or loss of control is initiated. Curves can present both roll and yaw instability issues to these types of vehicles due to varying heights of loads (low versus high, empty versus full) and road surface friction levels (e.g., wet, dry, icy, snowy) (Dunn et al., 2003*c*).
- Road design configuration — Drivers can misjudge the curvature of ramps and not brake sufficiently to negotiate the curve safely. This includes driving on ramps with decreasing radius curves as well as operating on curves and ramps with improper

signage. A vehicle traveling on a curve with a decrease in superelevation (banking) at the end of a ramp where it merges with the roadway causes an increase in vehicle lateral acceleration, which may increase even more if the driver accelerates the vehicle in preparation to merge (Jujnovic and Cebon, 2002).

- Sudden steering maneuvers to avoid a crash — The driver makes an abrupt steering maneuver, such as a single- or double-lane-change maneuver, or attempts to perform an off-road recovery maneuver, generating a lateral acceleration that is sufficiently high to cause roll or yaw instability. Maneuvering a vehicle on off-road, unpaved surfaces such as grass or gravel may require a larger steering input (larger wheel slip angle) to achieve a given vehicle response, and this can lead to a large increase in lateral acceleration once the vehicle returns to the paved surface. This increase in lateral acceleration can cause the vehicle to exceed its roll or yaw stability threshold (Liu, Rakheja and Ahmed, 1997; Ma and Peng, 1999; Jujnovic and Cebon, 2002; Rangavajhula and Tsao, 2008; Cheng and Cebon, 2008; Odhams et al., 2008; Islam, He and Webster, 2010; Kim et al., 2016). This method type is the most recommended and researched.

- Loading conditions — A loss of yaw stability due to severe oversteering is more likely to occur when a vehicle is in a lightly loaded condition and has a lower center-of-gravity height than it would have when fully loaded. Heavy vehicle rollovers are much more likely to occur when the vehicle is in a fully loaded condition, which results in a high center of gravity for the vehicle. Cargo placed off-center in the trailer may result in the vehicle being less stable in one direction than in the other. It is also possible that improperly secured cargo can shift while the vehicle is negotiating a curve, thereby reducing roll or yaw stability. Sloshing can occur in tankers transporting liquid bulk cargoes, which is of particular concern when the tank is partially full because the vehicle may experience significantly reduced roll stability during certain maneuvers (Chen and Peng, 2005).

- Road surface conditions — The road surface condition can also play a role in the loss of control a vehicle experiences. On a dry, high-friction asphalt or concrete surface, a tractor trailer combination vehicle executing a severe turning maneuver is likely to experience a high lateral acceleration, which may lead to roll or yaw instability. However, a similar maneuver performed on a wet or slippery road surface is not as likely to experience the high lateral acceleration because of less available tire traction. Hence, the vehicle is more likely to be yaw unstable than roll unstable (Jujnovic and Cebon, 2002).

Articulated heavy vehicles with their increased dimensions and weights are known to be high rollover risk vehicles. A number of studies have established that the dynamic roll instabilities are most frequently initiated at the rearmost of articulated freight vehicles and the driver often remains unaware of the impending instability. It has been recognized that some form of early warning to the driver on the onset of potential vehicle rollover is extremely vital to ensure road safety. The probability of heavy vehicle rollover accidents can be considerably reduced through on-line detection and early warning of impending roll instability, such that a corrective maneuver could be performed by the driver to avert the occurrence of a potential instability. Early detection of potential roll instability involves the establishment of a dynamic rollover criterion, and the identification of motion response parameters which are directly related to onset of vehicle rollover. Such vital parameters, however, must be directly measurable and relatively insensitive to variations in vehicle design and operating conditions to realize a reliable early warning system. Furthermore, the warning signals for impending rollover should be generated early enough such that the driver can perform the corrective maneuvers in a reasonable time. The design of a dynamic rollover warning device thus necessitates the identification of impending dynamic rollover indicators with high degree of measurability, reliability and available time margin for corrective

maneuvers.

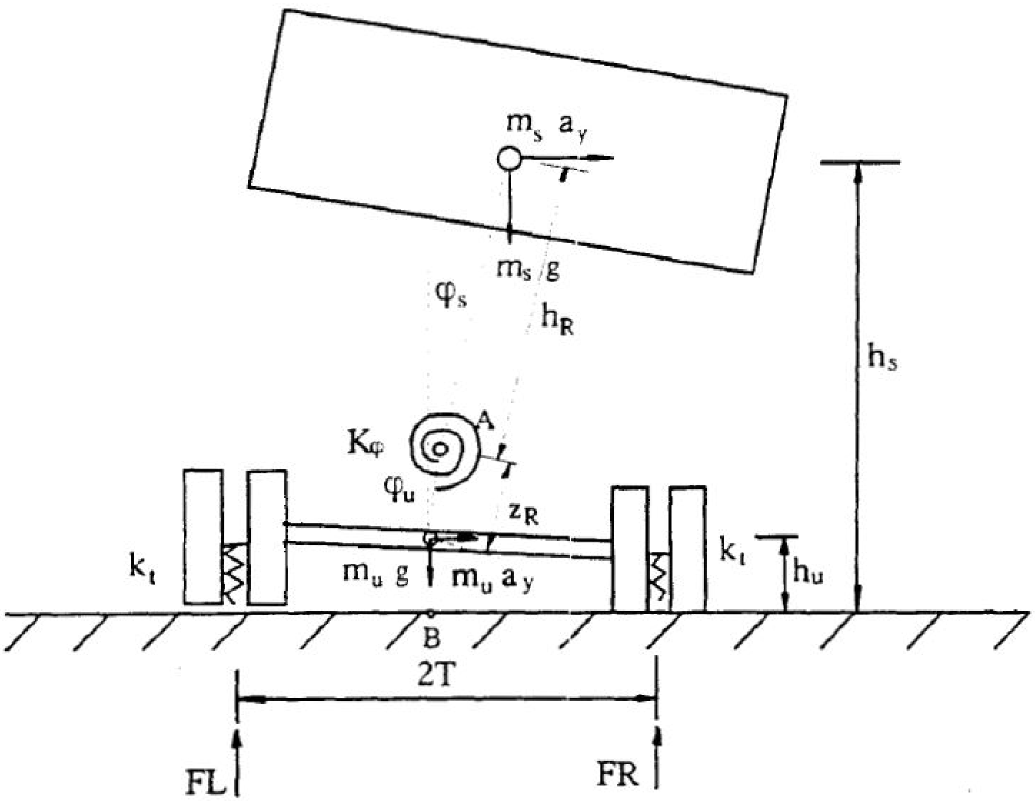

Figure 2.1: Lumped roll plane model of heavy vehicles

2.1.3 Jackknife Case

Jackknifing is a detrimental condition where a tractor (semi) truck becomes unstable and results in a large uncontrollable motion with high energy that almost always produces a crash with loss of life and significant collateral damage. Primary jackknifing causes are a combination of weather and high speed maneuvers such as a high velocity turn on a curve or a sharp braking impulse or

turn to avoid collision. Both of these primary causes are essentially due to low tire surface friction conditions where the driver rapidly loses control when the vehicle is at a high speed. (Dorion, Pickard and Vespa, 1989) generally specifies jackknifing as where the trailer maintains a straight linear path while the tractor rotates while under braking (perhaps excessive due to poor traction conditions) or under "power" braking when the tractor's rear wheels spin out when going downhill or on very low friction surfaces. These events occur most often in a rapid lane change or on a constant radius turn. Jackknifing occurs very suddenly around <0.5 seconds, leaving little warning to the driver.

A common truck driver response to an emergency is to brake significantly and rapidly. These are normal and natural human reactions. However such braking leads to a wheel lockup causing any truck imbalance to be exacerbated where tires lose more traction and the kinetic energy of the two connected bodies (tractor truck and trailer) become more unstable (less guided) (Dunn et al., 2003*b*).

These problematic conditions can be properly handled with real-time decision making that uses real-time data from a network of reconfigurable sensors distributed throughout the two vehicle bodies. Tracking kinetic energy flow in the two bodies is paramount to not only further understanding jackknifing but also for predicting and preventing jackknifing. Of primary sensing interest is where the

heading angle of both bodies begins to diverge while at high speeds (unlike a 90° turn after a stop sign/light). By definition, the physical meaning of jackknifing is a small time interval where the two linked bodies begin to diverge (become non-uniform) in direction or sense at high momentum, due primarily to high velocity. Measuring vehicle speed in tandem with body-to-body rotation or relative yaw provides a check for jackknifing potential (Bouteldja et al., 2006; Bouteldja and Cerezo, 2011).

The physical phenomena resulting from the primarily jackknifing conditions are sliding and trailer slewing or swinging.In the sliding case, which is common when a truck begins to decelerate without the trailer being aligned in heading (non-zero relative yaw) and an effective moment arm is formed that causes the trailer to skid outward causing a greater moment arm from the greater yaw angle. The driver needs to reduce the deceleration and steer the tractor into the skid or in a manner that reduces the relative yaw. Further braking will cause the relative yaw angle to increase and increase the moment arm that will lead to a worsening skid (Dunn et al., 2003*b*).

The trailer swinging case is primarily caused by high winds coupled with the high side surface area to catch drag on the trailer and the typical high center of gravity of the trailer. These factors cause the trailer to not be aligned with the tractor even when in

cruising conditions. These oscillations can grow to cause jackknifing (Dunn et al., 2003*b*; Azad, Khajepour and McPhee, 2005).

Once a jackknife is detected, real-time sensor data will be used to aid the truck driver in returning the vehicle to more stable conditions. The primary sensors of interest for this are: individual wheel traction and rotation speed, tractor and trailer planar accelerations (yaw and linear), tractor steering angle, and the throttle and brake state of the tractor.

Wheel measurements are especially useful because they provide information for traction management, since traction is at the root cause of jackknifing. Determining varying wheel rotations directly indicates unstable conditions while the driver still has an ability to take action. For the active wheel on the tractor, the differential in wheel torque provides insight to the actual ground surface condition (Odhams et al., 2008; Kim et al., 2016).

Determining when either vehicle body begins to have lateral kinetic energy is a primary indicator of general instability. Knowing the states of individual wheels, heading (steering angle), wind intensity, throttle, braking, an relative yaw will provide a means to develop a solution to the driver for reaching a safer condition (Kim et al., 2016). Driver fatigue in addition to mundane tasks such as determining the trailer oscillation can lead to lack of proper knowledge when a critical state materializes (Plchl and Edelmann, 2007).

Predicting and providing solutions to dangerous, fast response situations is the essence of a distributed real-time sensor network for smart truck driveltrains. Once such a system is in place, many possibilities for control systems emerge where the driver and operations managers can expand the scope of predictions and solution generations. Archiving for future enhancements will be possible with these systems, leading to deeper analysis of crashes and future insight on sensor tracking and control as well as vehicle and task modeling(Kim et al., 2016).

2.2 Smart Truck Operational Criteria

2.2.1 Wheel Force Management

The critical parameter to determine the maneuver capability of a modern open architecture vehicle is the wheel-surface friction coefficient μ for a wide range of surface and weather conditions. Here is outlined not only how to accurately obtain μ but also to manage all wheel forces to best control the motion of the vehicle in all motion commands (6 DOF in space) and in all classes of on and off-road terrains.

One of the most important parameters associated with the intelligent corner of open architecture commercial vehicles is real time awareness of the maximum tire contact force that is available to drive and maneuver the vehicle. This force is directly dependent on the coefficient of friction, μ. Decades of research by the vehicle community to create estimators for μ for tires on various surfaces show that they work both in simulation and experiment but with the severe penalty of deteriorating the wheel traction by using force disturbance functions that generate (otherwise unavailable) data in real-time for tire slip ratio/slip angle evaluation (Wong, 2008). Then, using known parameters such as wheel steer angle, camber, caster, angular velocity, tire pressure, etc., one could estimate the available longitudinal driving force (f_x) and the lateral sliding force (f_y) based on known tire performance maps (usually on a flat surface). Maps are frequently available for surface conditions such as moisture, water, snow, ice, gravel, etc. It is widely accepted today that in maneuvers (turns), GPS and INS (Inertial Navigation System) sensor data can measure the vehicle's dynamics, use that to calculate the expected slip ratio and slip angles and then knowing the expected inertia drift forces on the tires (to maintain the vehicle dynamics), and obtain an estimate for the associated friction coefficient μ. This approach demands full awareness in real time of the necessary maps (Wong, 2008) embedded in a local decision structure. Also, this approach presently works only with planar body motion which does not give us data on body pitch and roll (i.e., the real inertia force shift which requires 100 to 300 m-sec. to occur from the inside tires to the outside tires). Finally, none of this friction estimation works for vehicles operating at speed on the open road (to prepare for braking, to climb a hill, etc.) or off-road rough terrain.

In other words, there has to be a better way of knowing what tire forces really occur, and how close those forces are to being saturated (maxed out). This means what force margins are available to either increase or decrease our commanded speed or maneuver plan must known. Accurately obtaining friction coefficient μ is not only desirable, it is at the core of intelligent vehicle management (Ma and Peng, 1999).

An elementary representation of the tire contact force suggests that it creates a ***friction circle*** of forces which can be used to estimate the available driving force f_x and the lateral sliding force f_y, all depending on the coefficient of friction μ. Given an independently powered and steered wheel, the direction of that friction force f_w to best satisfy the commanded maneuver (i.e., generate the necessary global vehicle forces) can be arbitrarily chosen. But this depends on the knowledge of μ and the normal contact force f_N to generate $f_w = \mu f_N$. Given appropriate force sensors (in the suspension linkage or actuator motor current), the value of f_N can be commanded as needed depending on the capability (peak torque) of the active suspension actuator.

Given GPS and inertial sensors (INS), given tire performance

maps for all expected road conditions, and given f_N (by the active suspension); then it is possible to estimate slip ratio and slip angle to best estimate f_w, and at the same time a good estimate of μ (Jujnovic and Cebon, 2002). Knowing f_w, the vehicle controller will best select the wheel torque (to not exceed μf_N) and select the direction of the longitudinal tire force f_x and the lateral (sliding) force f_y.

Chapter 3

Smart Truck Sensor Synthesis

In this work for real-time data development for smart truck drivetrains, physical phenomena related to tractor truck control is identified and is the central focus for designing a sensing system. This chapter details the design of such a system given the detailed needs for the control of a complex mechanical system such as the smart tractor truck.

Chapter 1 presented why there is an immediate need to modify all the existing complex mechanical systems in favor of more intelligent systems, equipped with multiple sensors for informed decision making and intelligent operation to meet increasing performance demands. A goal of this document is to develop an argument to create a multi-sensor environment for complex mechanical systems such as tractor trucks.

3.1 Multi-Sensor Architecture Development

The advantages of multi-sensor systems are innumerable. Below is a list of relavent advantages:

- *Intelligent control in real-time using multi-criteria decision making:* Mechanical systems are becoming more complex in operation and in response to human demands. System nonlinearity is nearly impossible to control with classical control methods and is only marginally controllable with multivariable nonlinear or optimal control techniqes for a few degrees of freedom, which is not the case in the multibody tractor truck system. Such a system equipped with multiple sensors can determine the real-time state awareness and the operating conditions reducing uncertainty and predictive approximation (guessing) by the system controller. Further, sensor data uncertainty can be reduced with sensor fusion techniques. A multi-sensor system will enable intelligent control in real-time($\approx$ 10 m-sec.) to extract the best possible performance from the system to match constantly changing objectives and tasks (Tesar, 2016*b*).

- *Condition based maintenance (CBM):* A multi-sensor environment will allow continuous monitoring of system components, enabling detection of component degradation and signs of impending failures. CBM can, through design, assist in preemptive maintenance be relating historical system performance and component failures.

- *Performance maps:* A multi-sensor system provides a framework to enhance the characterization of effects of operating conditions on the system under operation. Performance maps highlight a mapping between measured data, indicating empirical relationships between parameters and operating conditions. More recent or improved (resolution) measurement data is used to update the performance maps previously obtained through analytical relationships or experimentation. Over time this approach refines parametric modeling of components and system.

- *Expanding safe operating regions to improve performance:* Typically system operation specifications are conservatively estimated because of a lack of real-time awareness about the states and the internal parameters during the system operation. This minimal information approach results in an underutilized system with imposed limits on system performance. A multi-sensor system with an extensive sensor suite and performance maps will provide a better awareness about the system during the operation, enhancing performance.

- *Distributed control:* A distributed control architecture gives advantages of flexibility and modularity/reconfigurability at the system level. This is achieved with control at the component or subcomponent level can be changed without affecting or making changes in the system level controller. The local controller has full knowledge of its connected component's real-time operating conditions.

- *Operational fault tolerance:* Multiple sensors will provide redundant information, which is used to reduce data uncertainty data and provide system fault tolerance. For example failure in a drivetrain bearing equipped with a vibration sensor (accelerometer), a temperature sensor and a microphone can be corroborated from the data from all three sensors. For sensor failures, the remaining sensors verify component operation to eliminates single point failures.

The first step in designing such a multi-sensor system is to determine the critical parameters of interest for desired system operation, such as tractor truck rollover or jack. Chapter 1 and 2 have defined a list of high interest operating conditions and their associated parameters along with and possible failure modes. In general, a nonlinear system will have various coupled parameters influencing the system operation where direct and real-time measurement is important for intelligent control and enhanced performance. To design a sensor network to produce a needed data flow, a review of how nonlinear phenomena affect the overall system behavior is needed to determine sensing requirements. Some parameters are essential to make informed judgments in intelligent control where as others are supplementary, but useful for redundant information (fault tolerance) and developing a better understanding of the system and components (performance maps).

Once sensing requirements are established, suitable sensor specifications need to be defined in a manner that balances, in the correct relative proportion, cost and benefit. Specifications include hardware parameters such as size (volume), weight, housing ruggedness and interface, etc. and sensing attributes such as resolution, accuracy, sensitivity, etc. Sensor capability should match the importance of a parameter.

One major point of interest should be the wide spectrum of sensing technologies. Various sensing technologies can sense physical phenomenon with comparable performance. For example the output angular position for an electro-mechanical rotary actuator can be sensed using hall effect sensors or optical encoders. A particular technology may be more effective than others in the required sensing environment. A comprehensive list of all the feasible sensing technologies with their pros and cons in the required application can make the evaluation and selection process more approachable (see Chapter 4).

3.2 Sensor Attributes

The selection of a particular sensor for the system depends upon the functional requirement, and the constraints on the sensing technology. For example, Time-of-Flight (TOF) technology is revolutionizing the machine vision industry by providing 3D imaging using a low-cost CMOS pixel array together with an active modulated light source. Compact construction, easy-of-use, together with high accuracy and frame-rate makes TOF cameras an attractive solution for a wide range of applications. However TOF technology does not work well outdoors unless advanced scientific sensors are used that will cost hundreds of dollars per sensor and are not yet mature for significant field use (Foix, Alenya and Torras, 2011). Proximity and laser based sensors provide equivalent information for low-cost and many commercial options. While these sensors may not have the resolution of TOF technology, these sensors are a better solution for the smart truck system.

Sensing requirements and desired sensor attributes change from application to application. In general, there are some basic characteristics desired in all the sensors. These attributes, include hardware features, sensing/measurement principles and data processing, data transmission properties, are used to evaluate sensors and sensor technologies. The following list details certain sensor characteristics used from selection criteria.

3.2.1 Sensing and Measurement Attributes

- Accuracy: A very important characteristic of a sensor is accuracy, which really means inaccuracy. Inaccuracy is measured as a highest deviation of a value represented by the sensor from the ideal or true value of a stimulus at its input. The true value is attributed to the input stimulus and accepted as having a specified uncertainty because one never can be absolutely sure what the true value is.

- Directly in terms of measured value of a stimulus.
- In percentage of the input span (full scale).
- In percentage of the measured signal.
- In terms of the output signal. This is useful for sensors with a digital output format so the error can be expressed, for example, in units of LSB (least significant bit).

Which particular method to use? The answer often depends on the application. In modern sensors, specification of accuracy often is replaced by a more comprehensive value of uncertainty because uncertainty is comprised of all distorting effects both systematic and random and is not limited to inaccuracy of a sensor alone.

- Precision: Accuracy and precision are often confused with precision being misunderstood. As defined above, measurement accuracy is the degree of closeness to the true value. Measurement precision is the degree of scatter of results (sensor readings) under the same conditions. This definition is equivalent

to the degree of measurement reproducibility or repeatability. Accuracy and precision are not interchangeable.

- **Calibration: The process of comparing instrument measurements against standard references with much greater uncertainty and condition control. Correction factors are determined from such comparisons. The reference source for calibration should be well maintained and periodically checked against other established references, preferably traceable to a national standard, for example a reference maintained by NIST (National Institute of Standards and Technology) in the U.S.A.**

- **Hysteresis: A hysteresis error is a deviation of the sensor measurement at a specified point of the input signal when the measurement is approached from the opposite or alternative directions. For example, a displacement sensor when the object moves from left to right at a certain point produces voltage, which differs from that when the object moves from right to left or at varying velocities. The typical cause for hysteresis is varying energy dissipation rates. This issue can be addressed in design geometry, friction, and structural changes in the materials, especially in elastic (soft) materials. In general, high quality machine design requires significant design in all three aspects.**

- **Nonlinearity: It denotes extent to which the actual measured curve of the sensor deviates from the ideal curve. Nonlinearity error is specified for sensors whose transfer functions may be approximated by straight lines, the simplest possible model. A nonlinearity is a maximum deviation of a real transfer function from the approximation straight line.**

  One important design consideration is "trimming" or specifying by design where a minimum nonlinearity error occurs in the most important target range. For example, a vehicle accelerometer should be designed for only motions for a target vehicle and not the entire spectrum of acceleration readings.

- **Sensitivity: In modern sensors, the relationship between input physical signal and output electrical signal. Sensitivity is expressed as the ratio of change in output signal to a small change in the input signal. It can also be defined as the minimum input of a physical parameter that will create a detectable output change, essentially the transfer function derivative with respect to the physical signal. High sensitivity is desired for sensors to minimize sensor power and space requirements. Additionally, high sensitivity results in a high signal-to-noise ratio providing greater immunity to electromagnetic noise (interference or transmission noise) than with a low-sensitivity device.**

- Dead Band: Essentially the opposite of a trimmed measurement range or point. Dead band is the insensitivity of a sensor in a specific range of the input signals. In this range, the output may remain at a constant value incorrectly over an entire dead-band zone.

- Saturation: Every sensor has its operating limits. Even if it is considered linear, at some levels of the input stimuli, its output signal no longer will be responsive. Further increase in stimulus does not produce a desirable output. It is said that the sensor exhibits a span-end nonlinearity or saturation.

- Resolution: The minimum detectable signal/stimulus fluctuation that can be detected. The resolution of a sensor with a digital output format is given by the number of bits, such as 8- or 16-bit resolution. In such cases the LSB is of interest. Sensor resolution is, in general, a direct trade off with cost.

- Measurement Range: The range of input physical signals that can be converted to a readable output signal. This range must match or exceed the expected operation variation.

- Response Time (Bandwidth): Sensors have finite response times to instantaneous changes in physical signals. In addition, many sensors have decay time, which is time after a step change in physical signal for the sensor output to decay to its original value. The reciprocal of these times represent the upper and the lower cutoff frequencies respectively. The bandwidth is the frequency range between these frequencies that can be captured and presented in the output when measuring a varying signal.

- Inherent Noise: An internal and substantial error source that is never eliminated but should be accounted for to minimize or prevent. Such error can occur from discretizing resolution (see Resolution), value drift, and low-quality circuitry generating unwanted electromagnetic effects. Interference (Transmission) noise will be discussed later.

- Sampling Rate: Refers to how fast the data acquisition system can sample for new measurement data. This is related to response time and bandwidth. A high sampling rate is highly desired and usually required in sensors for real-time/online monitoring and control (1 to 10 m-sec.). The simple Nyquist theorem requires a measurement frequency double the rate of system operation. The case for greater multiples in decision making applications will be discussed in Chapter 7.

3.2.2 Data Processing & Data Transmission Attributes

Signal from a sensor may be transmitted to a receiving end of the system either in a digital format or analog. In most cases, a digital format essentially requires use of an analog-to-digital converter at the sensor's site. Transmission in a digital format has several advantages, the most important is a noise immunity. In many cases, digital transmission cannot be performed or should not be, in the case of high quality demands. Then, the sensor output signal is transmitted to the receiving site in an analog form across various cable connect methods. Here are noise considerations to consider:

- Embedded Processing: Modern sensors are much more than simple transducers. Modern sensors have many embedded processes such as multiple sensing capability (temperature & pressure), signal processing and communication embedded in a single hardware package. Some higher capability sensors contain desired features such as signal conditioning and accuracy or sensitivity trimming.

- Interference (Transmission) Noise: External noise sources such as: power supply transients, electromagnetic, radio frequency, thermal, vibration, and humidity can cause significant or detrimental sensor operation. Interface circuits and built-in noise filtering circuits/algorithms should be used to mitigate these problems. This type of noise can be further reduced with cable and circuit enclosure shielding.

- Electric Shielding: Interferences attributed to electric fields can be significantly reduced by appropriate sensor and circuit shielding. Shielding serves to confine noise to a small region, preventing noise from spreading into nearby circuits. Shielding also serves to prevent noise from getting into sensitive portions of the detectors and circuits. These shields may consist of metal boxes around circuit regions or cables with shields around the center conductors. Standard shielding practices are detailed in *Noise reduction techniques in electronic systems* by Henry Ott.

- Communication Interface: Sensors with multiple standard communication interfaces/protocols are desired. Automatic detection in a network (plug and play, hot plugging) to ease maintenance effort should be considered.

3.3 Practical Approach for Multi-Sensor System Development

There are many solutions (sets of selected sensors) to satisfy multi-sensor system requirements. This should be treated as a constrained optimization problem where solutions that best match sensing and performance requirements and have the best benefit to cost ratio are selected.

Once the optimal sensor suite is selected, the sensors or sensor data flow needs to be integrated. Integration here refers to both, the physical sensor placement and the integration the different sensor measurement and ultimately various sensor operating time frames (see Chapter 7).

Physical integration also refers to connecting all the sensors to a controller or a network of distributed controllers using standard communication protocols. The idea is to use standardize interfaces and utilize common wires for multiple sensors to minimize communication complexity. This design work should include noise elimination, optimized data flow, and easy hardware debugging and calibration.

Once all the selected sensors are optimally placed and connected to respective controller(s), the next task is sensor data integration. This is the use of data from multiple sources to achieve the proposed goals of intelligent control, condition based maintenance, and fault tolerance. Integration of multiple sensory data sources can increase the confidence in actual state information and ensure robustness. This requires resolution of conflicting data for the same measurand obtained from different sources. Fault tolerance requires inference of lost data from other available resources. Various methods exist in information and estimation theory (Kalman filter, particle filters, Bayes reasoning etc.) towards integrating data from multiple sensors and inferring the lost data. (Ashok, Krishnamoorthy and Tesar, 2010) provided guidelines for managing multiple sensors by forming a network of sensors and taking advantage of relational nature (analytical relationships) of the diverse measurands.

All the functionalities and algorithms have to be encapsulated into a single software framework which will be the brain of the intelligent system. See Chapters 5 and 7 for more detail and for asynchronous data flow topics.

3.4 Examples of Multi-Sensor Systems

Development of a multi-sensor intelligent system is not a new field. A systematic approach for the design of instrumentation architecture and sensor data fusion concepts are shown to enable the robust control of complex electromechanical systems in flexible space robots (Stieber et al., 1998). Incorporation of multiple sensors in a complex system is evident in many fields, from nuclear reactors to air crafts. Although in many systems, real-time sensor data was not used in a manner to achieve direct intelligent control, primarily due to minimal sensor options and high sensor costs. Today, with enhanced computational capabilities and availability of low-cost sensing, multi-sensor intelligent systems can thrive because of feasibility to add more sensors into a dynamic system to improve real-time decision making. Recent developments of this are found in mobile robotics where platforms contain sensor suite including inertial measurement unit, range finder, cameras, multi-axis accelerometers, etc.

for navigation. Another field is the automobile industry where vehicles are equipped with an array of sensors to improve ride quality and safety.

Two detailed examples that design at the component level to get increased awareness, intelligent control are presented:

A multi-sensor architecture for electro-mechanical actuators was developed (Krishnamoorthy, 2005) with ten sensors embedded in an actuator, shown in Figure 3.1. These include angular position, velocity and acceleration sensors, torque sensor, temperature sensor, microphone, vibration sensor, magnetic flux density sensor, and current and voltage sensors. Inclusion of these sensors enabled intelligent control based on operating conditions and user set criteria. This system resulted in condition based monitoring of the actuators for incipient faults.

McFarland evaluated multi-sensor environment for monitoring (combat) soldier performance in real-time. The study assessed ten potential physiological indicators (sensors), termed biomarkers that correlate with human task performance condition (response to select set of stressors). These biomarkers include heartbeat, muscle activity, blood pressure, facial stresses, pupillometry, eye movements, skin response, temperature, and oxygen saturation. The focus was to monitor soldier performance in real-time by means of visual 3D performance maps supported by Bayesian network model

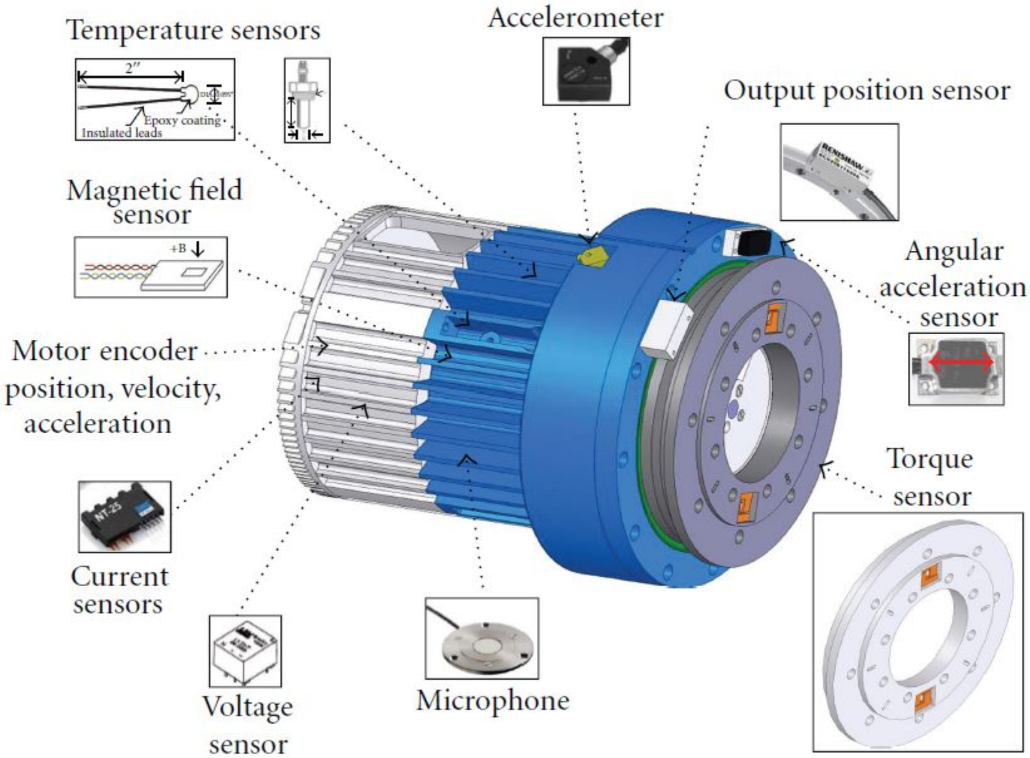

Figure 3.1: Electromechanical actuator with multiple sensors (Krishnamoorthy, 2005).

of soldier performance (McFarland, 2011).

Chapter 4

Sensors for Smart Truck Systems

Sensors form the foundation of any intelligent control scheme and determine the quality/extent of information available to levels higher in the hierarchy. Recognizing this significance, an analysis of the actuator sensing needs resulted in identification of ten principal sensing domains to initiate the creation of a multi-sensor architecture. This chapter details sensing requirements and possible relevant evaluation information such as appropriate technology and integration/synthesis.

4.1 Sensor Evaluation & Selection

A sensor, whether passive or active, establishes an interface between the physical environment of interest and a control system. Most sensors are no longer limited to being simple transducers and combine sensing, signal processing and communication hardware in a single unit. This provides a conditioned output, less susceptible to corruption by noise from transmission media or other sources. Their functionality is enhanced through such synergy by capabilities like compensation (for cross sensitivity, temperature effects etc.), auto-calibration etc. Sensor requirements refer to attributes desirable from an application standpoint. (Nettle, Tesar, 1991) established performance requirements for an array of robotic tasks and defined numerous attributes under four categories: global issues, performance issues, design/interface issues, fusion/software issues. However, there are no universal standards and various interpretations of performance parameters exist, which are specific to each sensor type. Acceptable values for each parameter depend on the physical principle the sensor is based on as well as the task requirements but there are certain basic characteristics that all sensors can be judged on.

4.2 Acceleration

4.2.1 Linear

Accelerometers and vibration sensors can be mounted at multiple locations on a trailer to measure motion amplitude and frequency. It is desired that the operating range spans the accelerometer's measurement range to get maximum sensitivity to target motion acceleration range (frequency).

A three axis accelerometer on the trailer body can capture the response of the trailer as a rigid body due to decelerations, braking and road curvatures. This accelerometer should be operating at $\pm$2g range to sense low frequency oscillations such as lateral sliding – the primary cause of rollover and an initial condition for jack-knifing – and oscillations due to road irregularities along with truck suspension degradation. Extensive modeling, empirical data and simulation results from these works (Liu, Rakheja and Ahmed, 1997; Winkler and Ervin, 1999; Cheng and Cebon, 2008) indicate the importance of lateral linear acceleration in this range. An accelerometer on the trailer body can also complement an onboard gyroscope to measure tilt or inclination of the trailer.

An accelerometer on the bearing adapter or near wheel/axle should be able measure high frequency vertical vibrations and impact forces 300g coming from wheel and road interaction. This accelerometer can monitor for bearing defects and irregularities in the ground interface (wheel components), etc (Matzan, 2007).

Conceptually an accelerometer behaves as a damped mass spring system. The mass is displaced relative to the accelerometer mounting, causing deflection in the internal spring element. Piezoelectric, piezoresistive or capacitive elements convert mechanical motion into an electrical signal. Modern accelerometers are low cost sensors based on MEMS technology. These accelerometers provide user selectable measuring range and bandwidth (user set filter components) with very little power consumption. They are small size (a few millimeters) and can be integrated on a circuit board with other sensors, a micro-processor and data transmission circuit.

Linear accelerometers are inertial sensors, which do not require referencing to a stationary coordinate system. They are attached to moving platforms. In navigational devices, accelerometers work together with gyroscopes, typically containing three orthogonal rate-gyroscopes and three orthogonal accelerometers, measuring angular velocity and linear acceleration, respectively.

4.2.2 Rotational

A gyroscope measures rate of angular rotation. A gyroscope on the trailer can provide yaw, pitch and roll rate of the trailer body. The angular velocity data can be integrated to get the angular position which can give a measure of tilt or inclination of the trailer. GPS is not reliable for safe distance measurement between other vehicles (even if other vehicles are tracked with GPS) as the GPS information is not accurate enough, at least in real-time, to realistic relative distances closing rapidly (Bouteldja et al., 2006; Cheng and Cebon, 2008). GPS has especially insufficient accuracy in complex terrain such as by city buildings and in tunnels. Location sensors are used on the truck body for this purpose but they do not give real-time information about truck speed and acceleration. Thus an onboard gyroscope can be useful in augmenting the GPS data for accurate position awareness of the truck.

Modern day gyroscopes are tiny low-cost sensors based on a vibrating structure manufactured with MEMS technology. Similar to MEMS accelerometers, these are small (few millimeters) packaged like integrated circuits and provide an analog or digital output. They can typically be integrated with linear accelerometers.

4.3 Inertial Measurement

An Inertial Measurement Unit (IMU) integrates a multi-axis accelerometer, a single or multi axis gyroscope and optionally a magnetometer to track the motion of a rigid body. An IMU on a vehicle platform can give position, orientation, velocity and acceleration of the vehicle. The control input to the vehicle actuators and the wheel terrain interaction directly governs the motion of the vehicle. The IMU data indicating the actual motion of the vehicle can be used (as a feedback) to compute new control input to meet the desired trajectory and required vehicle performance. The IMU data is important in stability control and evaluation of ride quality. IMUs on vehicles can complement GPS or can work stand-alone when the GPS signals are unavailable.

Low-cost MEMS based IMUs are available from a variety of manufacturers such as SBG Systems, VectorNav Technologies, Gladiator Technologies, Rockwell, Honeywell, Fairchild, Texas Instruments (TI), and Analog Devices (ADI). They include a processor chip and a signal conditioning unit which can filter raw data from individual sensors and combine data using sensor fusion techniques to give final position, velocity and acceleration in 6 degrees of freedom. This embedded processing capability reduces computational load on the central computer.

4.4 GPS

The Global Positioning System (GPS) is a satellite-based navigation system that works in any weather condition, anywhere in the world, 24 hours a day. There are no subscription fees or setup charges to use GPS and commercial systems can be accurate up to less than 3 meters on average (Bouteldja et al., 2006; Cheng and Cebon, 2008).

4.5 Steering Angle

The Steering Angle Sensor (SAS) is intended to be used in making adjustments and corrections for vehicle stability by counting the revolutions that the steering wheel is making and how fast and compares those numbers to a set of standards.

Here is an example of how an SAS is used in vehicle stability: As a driver steers a vehicle, the steering angle sensor will send signals to the ECU (Electronic Control Unit). The ECU will determine the vehicle heading and the speed the steering wheel is turning. Remember that as a vehicle enters a curve, all tires move at different rates where the inside tire rotates at slower speed than the outside tires. In an understeer condition, traction is lost on the front wheels, causing the vehicle to make a wider turn and that causes a speed difference to decrease between the right and left front wheels. In an oversteer condition, the rear wheels loose traction and the vehicle begins to spin and the speed difference between the right and left tires to increase. The SAS will continuously send real-time data to the stability control software (located in the ABS Control Module) that will begin to apply brake pressure to the appropriate wheels to counter the forces involved. Furthermore, the engine power can be reduced and the vehicle should regain stability.

Unfortunately, as discussed previously, common commercial vehicle control systems solely rely on passive or energy removal methods so alternative, active control or energy input in synchronized pulses are not considered.

4.6 Grade Inclination

An inclinometer is an instrument for measuring slope angle (or tilt), elevation or depression of an object with respect to gravity. An inclinometer is also known as a tilt meter/sensor, tilt indicator, slope alert, slope gauge, gradient meter, gradiometer, level gauge, level meter, declinometer, and pitch & roll indicator.

4.7 Wheel Torque

Wheel torque sensor measures torque applied to the wheel or the reaction torque on the wheel. The wheel torque data can be of great interest during off-road driving, braking and speed coast down. It can give an idea about the required (or actual) energy the vehicle/actuator has to provide to overcome the tire rolling resistance. The difference between the motor output torque and the wheel torque gives an estimate of driveline resistance and mechanical efficiency. Wheel torque sensors are used during vehicle dynamic testing. It is now suggested to use them during the normal vehicle operation and get real-time torque data from each wheel. Wheel torque is one of the primary input parameters in traction control. Real-time wheel torque feedback is essential for intelligent control of the vehicle based on operating conditions (minimize wheel slippage for higher efficiency).

Wheel torque sensors are typically rotating strain gages on an adapter plate mounted to the wheel rim or bolted to the brake drum or spindle of a truck trailer. Temperature compensation is provided in most commercial sensors. A careful design can provide immunity to radial and cornering loads and reduce vulnerability to impact load from wheel terrain interaction. Electrical signals are transmitted either through slip rings or via non-contact rotary transformer. Slip rings are more prone to wear due to friction contact and are subject to intermittent connections and limitations on the rotational speed. Some sensors also provide non-contact telemetry signal transmission to the data acquisition instrument inside the vehicle.

4.8 Wheel Speed

A wheel speed sensor is used to measure the rotational speed of a vehicle's wheel. A wheel speed sensor is a hub-mounted sensor and typically uses a toothed wheel on the axle drive shaft. Variable reluctance wheel speed sensors use a magnet and a coil of wire (magnet pickup) to generate an analog (alternating) signal. The voltage level is dependent upon the rotational speed of the wheel. A Hall effect wheel speed sensor uses a toothed wheel and generates a square wave signal with frequency proportional to the speed of the wheel. Hall effect sensors need excitation power.

Wheel speed sensors are used in almost all modern vehicles now as a part of the Anti-Lock Braking System (ABS). In ABS, for four wheeled vehicles, four speed sensors monitor the wheel speeds and check for possible wheel lockups and uncontrolled skidding (one wheel rotating significantly slower or faster than other wheels). The brake hydraulic valves are actuated to reduce or increase the pressure controlling the braking force on the affected wheel.

The ABS is proven to be extremely useful improving vehicle control and decreasing stopping distances on dry and slippery surfaces. The proposed use of the wheel speed sensor is not only during braking but it can be used continuously to evaluate the wheel-surface interaction. Wheel rotational speed is used to calculate the linear speed of the surface contact point or contact patch $(R\omega)$. The vehicle ground speed and the wheel contact point linear speed gives data to compute wheel slip - an important parameter in traction control.

4.9 Wheel Force

The multi-axis wheel force sensor is used to measure all dynamic forces and moments on a wheel in real time. The wheel force sensor will provide independent output signals for vertical, lateral and longitudinal load on the wheel as well as camber, steer and torque moments acting on the wheel. Vehicles can be analogous to robotic systems with each wheel corner interpreted as a four degree of freedom robotic arm providing active steering, camber, active suspension and drive torque. In an intelligent vehicle, it is desired to know individual control of forces at all wheels at all times. From this analogy, a wheel load sensor provides useful information about the wheel's interaction with the terrain, quite similar to a force-torque sensor at the end-effector of a robotic arm that measures interaction

forces with the environment. The wheel force transducer data can be used in stability control, active suspension, traction improvement (traction torque component) and impact load measurements.

Wheel force transducers are strain gage bridge modules which typically mount between vehicle hub and the wheel rim. The sensing elements rotate with the wheel and slip rings or a non-contact rotary transformer is used to transmit signals to a stationary signal conditioning unit. The forces are required with reference to a coordinate system fixed to the vehicle. The rotating electronics package also measures angular position required to transform the force and torque vectors into a non-rotating frame of reference (vehicle's coordinate frame). The six components of the total wheel load are structurally decoupled to provide independent outputs. National Highway Traffic Safety Administration (NHTSA) uses wheel force transducers are used in vehicle testing and for road load measurement. It is now recommended to use them on all wheels at all times for intelligent vehicle control (Dunn et al., 2003*c*).

Wheel force and torque transducers primarily use strain gage bridges to measure torques and forces acting on the wheel. Strain gages are low cost sensing elements but proprietary hardware, signal conditioning, and communication and data acquisition units make all current commercial wheel torque transducers too expensive or too unreliable for wide use (Stefanescu, 2011). There is a pressing need

to standardize these sensors and make a unifying open platform to connect analog and digital sensor output signals to a modular DAQ device on the vehicle. This will drive the sensor cost down and make a multi-sensor system feasible in all complex mechanical systems like vehicles.

4.9.1 Tire Pressure

Pressure sensors can be used to monitor the tire pressure in real-time. Tires lose air pressure due to leakage and seasonal temperature variations. Most modern vehicles now have a direct tire pressure monitoring system (TPMS). But in the current system tire pressures are gauged infrequently and the vehicle operator is given no real-time visual information until the pressure in the tire has become critically low. It is recommended to measure the tire pressure in real-time and use it actively in traction control.

As the generality of vehicles expand, intelligent vehicle operation necessitates active control of tire pressure based on road surface characteristics to get maximum available traction. The optimum tire pressure is different for on-road and off-road conditions. Real-time tire pressure information can be used in intelligent control of the driving actuator to get optimum performance in given conditions. Active tire pressure control improves traction performance, increases tread life, reduces vibration and shock loading in off-road conditions, increases fuel economy, improves vehicle safety and reduces downtimes associated with tire maintenance.

Pressure sensors are typically located on each wheel's valve stems (typically screwed) to directly measure the pressure in each tire. Modern MEMS pressure sensors based on capacitive technology also integrate a temperature sensor, accelerometers to detect motion, a microcontroller (MCU), a radio frequency (RF) transmitter all in one package.

4.9.2 Tempurature

Temperature sensors can be used at multiple locations on a trailer. Defects in the moving components typically result in a rise in their temperature as the mechanical energy is converted to the heat energy because of friction losses and impact forces. In truck operation, bearing defects increase the temperature in the bearing cup and on the adapter surface. Temperature sensors can be used to monitor the condition of these components in real-time and raise a precautionary alarm for any signs of overheating and degradation. Moreover, some goods (food, chemicals) require controlled temperature during their storage and transportation. A low cost temperature sensor can be used to monitor the condition inside the trailer.

The most critical use of the temperature sensor is for real-time monitoring of trailer bearing health. The bearing temperature is almost equal to the ambient temperature during normal operation. Defects in the bearing induce vibrations and friction losses which heat up the bearing cone raising its temperature. The bearing temperature can go as high as 150°C above the ambient temperature indicating the risk of complete failure (Hayes, 2004; Matzan, 2007).

4.10 Throttle

A throttle position sensor (TPS) is a sensor used to monitor the throttle position of a vehicle (Markyvech, 2006). The sensor is usually located on the butterfly spindle/shaft so that it can directly monitor the position of the throttle. More advanced forms of the sensor are also used, for example an extra closed throttle position sensor (CTPS) may be employed to indicate that the throttle is completely closed. Some engine control units (ECUs) also control the throttle position electronic throttle control (ETC) or "drive by wire" systems and if that is done the position sensor is used in a feedback loop to enable that control.

Modern day sensors are non-contact type. These modern non contact TPS include Hall effect sensors, inductive sensors, magnetoresistive and others (Hiligsmann and Riendeau, 2003). In the potentiometric type sensors, a multi-finger metal brush/rake is in contact with a resistive strip, while the butterfly valve is turned from the lower mechanical stop (minimum air position) to wide open throttle (WOT), there is a change in the resistance and this change in resistance is given as the input to the ECU.

Non-contact type TPS works on the principle of Hall effect or inductive sensors, or magnetoresistive technologies, wherein generally the magnet or inductive loop is the dynamic part which is mounted on the butterfly valve throttle spindle/shaft gear and the sensor & signal processing circuit board is mounted within the ETC gear box cover and is stationary. When the magnet/inductive loop mounted on the spindle which is rotated from the lower mechanical stop to WOT, there is a change in the magnetic field for the sensor. The change in the magnetic field is sensed by the sensor and the voltage generated is given as the input to the ECU.

4.11 Braking

Pedal-force load cells are commonly used in cars and trucks to measure brake-pedal force measurement and as a high-precision trigger for brake-testing equipment. Though specifically designed to measure the force needed to operate a vehicle's brake, clutch, or floor-mounted emergency brake pedals, Pedal-force load cells are adaptable to measure any pedal-based pressure.

Such a measurement is useful in determining a solution to recommend to the driver involving the brakes. For example, information to determine if the driver should brake more or less cannot be determined solely from linear acceleration.

4.12 Yaw Rotation

The Yaw rate sensor measures the rotation rate of the car probably using a rotating accelerometer or a 3 DOF gyroscope. In other words, the sensor determines how far off-axis a car is "tilting" in a turn. This information is then fed into a control system that compares the data with wheel speed, steering angle and accelerator position, and, if the system senses too much yaw, the appropriate braking force is applied (again, not the passive approach). The lateral acceleration sensor (accelerometer) measures the g-force from a turn and sends that information also to the ECU.

4.13 Strain

When force is applied to a compressible resilient component, the component is deformed or strained. The degree of strain (deformation) can be used as measure of displacement under influence of force. Thus, a strain gauge serves as a transducer that measures a displacement of one section of a deformable component with respect to its other part. Strain gages are widely used as primary sensing elements for force and pressure measurements. They are typically based on the principle of change in resistance of the gage material

(conductor) due to deformation.

Strain gages can be used at multiple locations on a truck trailer to give information about dynamic loading and impact forces on the trailer body and the trailer components. The tractor truck fifth wheel can be outfitted with strain gages to measure longitudinal forces resulting from braking, acceleration, and jerks in the train consist in the longitudinal direction. Shear gages mounted on the sides of the fifth wheel can measure vertical coupler forces arising from road irregularities. Wheels can also be instrumented with strain gages to measure vertical, lateral and longitudinal forces at the wheel/road interface. These forces indicate impact/shocks on the truck due to road irregularities.

Typical strain gages are slender (wire like) metallic resistive elements which change resistance, on compression, or elongation (resistance is directly proportional to the length and inversely proportional to the area of the element). A typical piezoresistive strain gauge is an elastic sensor whose resistance is function of the applied strain. Since all materials resist to deformation, applied force determined from deformation. Hence, electrical resistance can be related to the applied force.

4.14 Sound

A microphone is a pressure transducer adapted for transduction of sound waves over a broad spectral range that generally audible. Microphones differ by their sensitivity, directional characteristics, frequency bandwidth, dynamic range, sizes, etc., and can be used for monitoring a bearing's health based on the acoustic signature of the bearing during operation. Acoustic signals from defective bearings have peaks at frequencies higher than the rotational rate of the bearing, hence, continuous condition monitoring is possible. An acoustic sensor near the brake may also be very useful.

The dynamic range and frequency response are two of the most important parameters in the selection of an appropriate microphone for a given application. Dynamic range is the range of sound pressure levels (dB) for which a microphone meets its performance specifications. Higher dynamic range ($\sim$150 dB) is required in the continually loud road environment (Smith, 2013; Norton, 1989).

A microphone near a bearing will experience a wide range of acoustic frequencies. Low frequency components from an aerodynamic bow wave can be rejected with a high pass filter (rejecting less than 8 Hz but still allowing low frequency audible signals $\sim$20Hz). Acoustic signals from defective bearings show peaks at frequencies corresponding to the defect repetition rate (30 Hz to 100 Hz). High frequency sounds (>15 kHz) were also distinctly observed in acoustic signals coming from defective bearings (Smith, 2013; *Practical Design Techniques for Sensor Signal Conditioning*, 1998; Matzan, 2007). A microphone with high frequency range (dc to 40 kHz) is most desirable (as used in wayside inspection). A low-cost microphone in the audible range (20 Hz to 20 kHz) may also be sufficient for bearing condition monitoring. High sample rate (>80 kHz) is required to fully support high frequency content. A good signal to noise ratio (>40dB) and a wide operating temperature range is desired (Matzan, 2007).

4.15 Proximity

A proximity sensor detects the presence of an object in the 'vicinity' of the sensor. A position sensor measures distance to the object from a certain reference point, while a proximity sensor generates output signals when a certain distance to the object has reached. Vicinity is defined as the distance from the sensor to where a target object is detectable.

A proximity distance sensor can be used to evaluate the brake piston travel in real-time. Currently the truck industry does not have a mechanism to determine whether brakes are applied effectively in real-time, a serious safety concern. A simple low-cost proximity sensor can measure the brake piston stroke and relay the information to the truck driver in real-time. The sensor can also indicate potential wear on a brake shoe for preventive maintenance.

Proximity sensors are based on variety of operating principles. Inductive proximity sensors are based on electro-magnetic induction and are best suitable for metallic objects. Capacitive proximity sensors use variation in capacitance between the sensor and the object. They can be used for non-metallic objects like plastic or wooden materials. Infrared proximity sensors use beam reflection and changes in ambient conditions to allow sensing of the objects and measure object distance. Ultrasonic range finders emit sound waves (ultrasonic) and measure time of flight to estimate the object distance. Infrared and ultrasonic proximity sensors typically have larger range.

For the truck's pneumatic brakes, piston travel must provide brake shoe clearance when brakes are released. A low-cost infrared or ultrasonic based proximity sensor with suitable range can be chosen for real-time monitoring of brake piston travel and brake effectiveness. These sensors are placed under the trailer and are subjected to debris, wide range of temperature and contact with snow, dust, water and oil. The system design should be rugged and useful in all weather conditions.

4.16 Onboard Sensor Power Requirements

In general, a multi-sensor system should be designed to use as many sensors as possible to enable as much system awareness about a truck trailer's operational conditions as possible. However, this sensor array will require a continuous and reliable source of electric power for operation. Current tractor trucks do not run such a local power grid through the truck so a primary concern is to have a local power source on each trailer and possibly an onboard low-cost energy harvester to energize an onboard battery pack to assist high demanding power tasks such as data transmission (Mickle, Capelli and Swift, 2006). The onboard energy harvester should be low-cost, reliable and be able to retrofit into existing systems and should be an add-on module to the desired sensors.

Most energy harvester designs convert kinetic energy of the axle/wheel or trailer to electric energy. Dana Corp., a tractor truck manufacturer, is developing a special generator bearings (wheelset generators), which integrate into the existing axle box housing. They consist of a modified axle cover acting as a rotor and the housing acting as a stator. This class of harvester tends to be expensive and hard to maintain. Some bearings are also equipped with a temperature sensor and an accelerometer and transmit data over radio frequency to a receiver on the trailer.

Solar energy and wind energy are also potential options. They can keep the onboard accumulator (batteries) charged even when the truck is stopped and no kinetic energy is available. Alternative energy sources are unreliable (night time, city driving, etc.) and

should only be considered as a supplemental source.

To reduce the power requirements, self-energizing or low power consuming sensors are preferred. Many sensors have an idle state or sleep mode where the power consumption is minimal when no measurements are taken. In addition to the sensors which measure raw data, data processing and data transmission units may require additional (20 to 30) watts of power. Wireless transmission (WiFi, Bluetooth, ZigBee, etc.) units are power hungry. Wireless power transmission should be considered (Le, Flez and Mayaram, 2009; Butler, 2012; Safak, 2014). Appropriate sampling frequency, efficient information flow and data management (from individual sensors to a microchip on the trailer to the truck) can greatly reduce power consumption.

Chapter 5

Sensor Data Monitoring & Fusion

Multiple sensors deployed onboard a tractor truck provide a wide variety and large amount of data that is crucial to manage correctly in real-time to convert into useful decision making information. Embedded sensors can be grouped based on the information they give on a specific component or domain in a tractor truck system. Obviously sensors are inherently noisy and data from multiple sensors can be integrated or correlated to increase confidence in the measurements so various data filtering/processing methods, such as information and estimation theory (Kalman filter, Bayes reasoning, etc.), should be implemented. This ensures proper data integration from multiple sensors and enables inferring the lost data resulting to provide fault tolerance and eliminate single point failures. This chapter details this information and provides references and examples for the foundation of system intelligence for tractor trucks.

5.1 System Intelligence

Sensor management typically refers to scheduling and activating the appropriate distributed sensor(s) to address issues like power usage, limited bandwidth, data mismatch or in the context of target tracking where it refers to the process of selecting appropriate sensors, to optimize their effectiveness in characterizing the probability of a target occurring in a region under consideration. The common thread in the examples below is that application specific criteria are used to make decisions on what sensors to use, when, and for what purpose.

- For continuous condition monitoring for a bearing, an accelerometer, a microphone and a temperature sensor are used where each sensor can individually detect bearing defects. The bearing condition can be estimated by weighing data from each sensor based on their accuracy and sensitivity to the bearing defects. For example, temperature may be normal at an early stage of the defect. But acoustic and vibration signals can indicate impending bearing failures. Similarly some defects may not result in distinct vibration pattern but the bearing cup temperature may rise. A Kalman filter can be used to fuse all sensor data. Note that the measurements from the three sensors can be asynchronous and at different sampling frequencies.

Analytical or empirical relationships among sensor data can be used to generate a Bayesian network of all bearing sensors. Historical data can be used to discard outlier measurements to reduce false alarms.

- Onboard gyroscope and accelerometer data can be integrated to determine turn curvature. Angle/tilt estimation by integrating gyroscope output accumulates null bias error as the integration period is increased. The gravity signal from an accelerometer can be used to correct the inclination measured using a gyroscope. The gyroscope and the accelerometer together can accurately over time sense truck orientation and the flow of kinetic and potential energy through the tractor truck system.

- Similar to the bearing setup, the brake sensor system can consist of a proximity sensor, a microphone and a pressure sensor. The proximity sensor can measure the brake piston travel. The microphone may indicate braking performance via acoustic signature. The pressure sensor can monitor cylinder and valve pressure with low pressure meaning poor braking force. Experimental data from all three sensors during normal braking operation and in tests with induced faults can help correlate sensor information. Lost data due to a sensor fault can be inferred using these correlations; thus providing multiple ways to assess the condition of the braking system (Krishnamoorthy, 2010).

- Trailer load on the can be directly measured using a load sensor placed on suspension springs on trailer axles. Proximity sensors on the bolster can measure suspension coil compression to give an estimate of the load. Proximity sensors on both sides of the trailer can give information about load distribution and can corroborate dynamic response measurements (roll and pitch) from onboard accelerometers and gyroscopes.

- Trailer component condition and behavior depend significantly upon trailer speed and loading. A defective bearing will heat up faster for a fully loaded trailer than for an unloaded one. Impact forces due to wheel and road irregularities are higher at higher vehicle speeds. An intelligent system should take all these factors into consideration (temperature, speed compensation) during condition monitoring of a trailer and the potential for raising an alarm for faults.

Many of these applications use criteria/norms derived from the field of information theory in combination with some form of estimation theory such as Kalman filter (Wang and Qin, 2016; Xing and Xia, 2016). Alternative approaches include Bayes reasoning, neural networks, fuzzy logic techniques and a rules/knowledge database to estimate the reliability of sensor readings (Khaleghi et al., 2013).

Although each method has its own advantages (speed, accuracy, ease of implementation, etc.) and weaknesses (need for a system of mathematical models/equations, inability to detect multiple sensor faults, inability to distinguish between sensor and system faults, need to integrate different approaches together in the same application in order to accomplish different tasks like modeling, fault detection, fault isolation, etc.) (Khaleghi et al., 2013; Krishnamoorthy, 2010) the focus of this work is to use the Bayesian causal network framework to accomplish these goals. This approach can provide a unified, data-driven framework for correlating the system variables in a physically meaningful manner (that can also be represented graphically for intuitive understanding) as well as perform fault detection, isolation, and fault accommodation using the same framework. In addition, the existence of a well-developed mathematical formalism based on probability theory helps account for the nonlinearities and uncertainties associated with the system under consideration.

The primary objective in creating the network is to combine information from distinct, nonredundant measurements and provide information fault tolerance. An example system with multiple sensors is an electromechanical actuator (EMA), shown back in Fig-

ure 3.1, fitted with sensors measuring eleven different phenomena: current, voltage, acoustic noise, torque, angular acceleration, output speed, output position, vibration, temperature, magnetic field, and motor position encoder (Krishnamoorthy, 2005). This example work resulted in all eleven phenomena measured are linked directly or indirectly to all other sensors, illustrated in Figure 5.1. Another possible sensor network is shown in Figure 5.2.

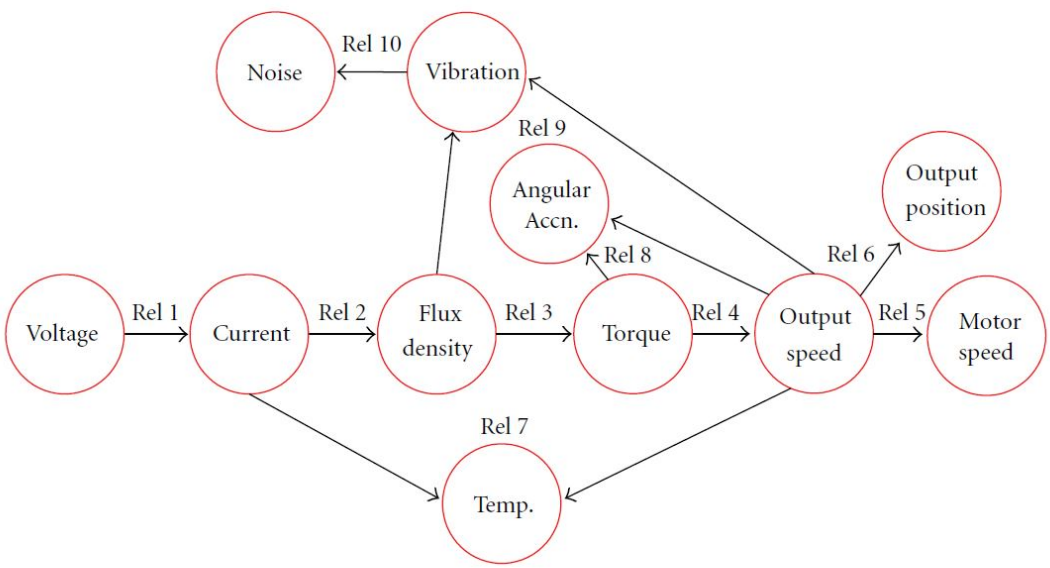

Figure 5.1: An arbitrary network that uses 10 analytical relationships (Krishnamoorthy, 2005).

There can be many different ways in which the sensors may be linked to provide for fault tolerance. There is currently no unified set of guidelines to aid in the selection of one network configuration over another.

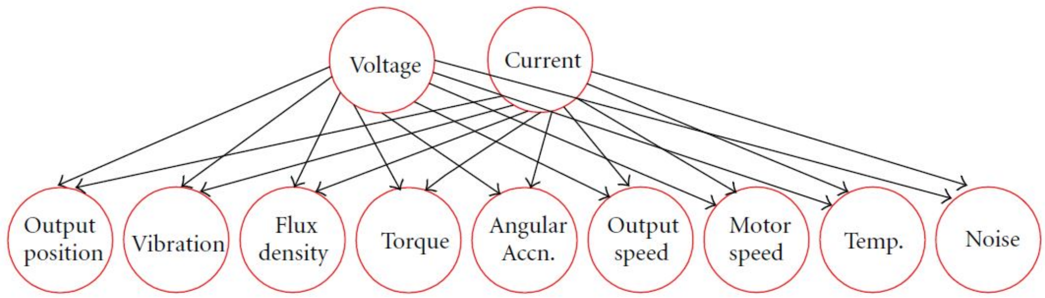

Figure 5.2: Another network that satisfies the same functions (Krishnamoorthy, 2005).

In this chapter, the following two questions are addressed for such a intelligent multi-sensors system:

- **What is the best way to relate various sensors information?**
- **How can human decision makers use a network for maximizing system performance in real-time?**

The inclusion of sensors in a system provides many advantages as discussed, but it comes with a separate set of issues such as: physical integration, cabling complexities, sensor noise, communication, data management, maintenance, and integration cost.

A major issue is interfacing the sensors with an embedded controller. The associated wiring complication is an important factor in the selection of network architecture for the system. Although wireless sensors are an improved option, they require additional hardware and typically are power hungry. In a multi-sensor system,

connecting every sensor individually to the central processor results in large number of cables, unacceptable in most commercial applications. Long running cables in a noisy environment makes data susceptible to corruption.

A distributed or decentralized structure greatly reduces communication (and cabling) complication and offloads computational demands from the central processor for increased response time. Local processors handle raw data from sensors and transmit only useful information to the central processor. The sensor network architecture (hardware, communication and software) must be modular, provide easy access to data and should require minimum effort for augmenting capabilities for future task demands.

This chapter contains methods on developing proper data flow for decision making logic structures, which are discussed in Chapter 7.

5.2 Advances in Sensor Technology

A sensor converts the physical quantity of measurement interest into a readable (electrical) signal for data processing. Traditionally sensors were just transducers, which sensed (interfaced with) a physical phenomenon and output raw streams of data. A central processor needed to perform tasks such as amplification, filtering, bias correction and A/D conversion to interpret signals and obtain meaningful information. To do the same for all the sensors demands significant processing capabilities on the central processor.

Modern sensors embedded into various systems today generate different types of electronic signals such as analog voltage, analog current, frequency modulated or digital signals. Modern control systems require digital information, which is typically acquired by converting analog signals into digital information using standard quantization processes (Kester, 2010).

Today's engineer faces a challenge in selecting the proper mix of analog and digital techniques to solve the needed signal processing task at hand. It is impossible to process real-world analog signals using purely digital techniques, since all sensors, including microphones, thermocouples, strain gages, piezoelectric crystals, and disk drive heads are analog sensors. Therefore, some sort of signal conditioning circuitry is required to prepare the sensor output for further signal processing, whether it be analog or digital.

Signal conditioning circuits are analog signal processors, performing such functions as multiplication (gain), isolation (instrumentation amplifiers and isolation amplifiers), detection in the presence of noise, dynamic range compression, and filtering (both passive and active). Several methods of accomplishing signal processing are shown in Figure 5.3. The top portion of the figure shows the purely analog approach. The latter parts of the figure show the DSP approach. Note that once the decision has been made to use DSP techniques, the next decision must be where to place the ADC in the signal path.

Once analog signals have been conditioned, the next step is digitization. Analog to digital converters (ADC or A/D converter) are a critical part of a data acquisition system because this step primarily determines the initial data accuracy and precision before any data filtering/processing algorithms perform. Aside from sensor sensitivity and accuracy, these converters essentially determine the overall data quality (poor converters means poor data extracted).

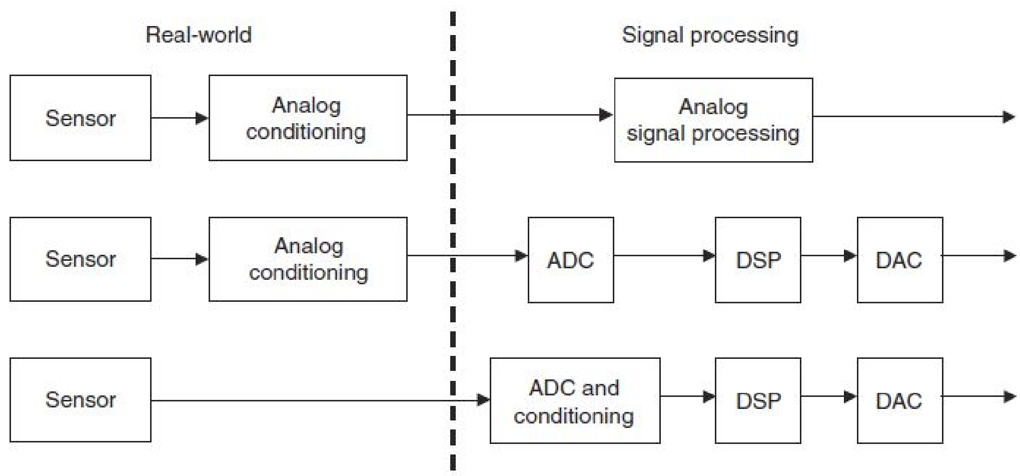

Figure 5.3: Analog and digital signal processing options (Bensky, 2004).

An intelligent or *smart* sensor should include (have embedded or built-in) computational capability and communication hardware in a single package in addition to the sensing capability. Raw analog

signals are processed and their digital representation is transmitted via standardized communication protocols by the sensor itself instead of a distributed system of individual components performing these tasks individually. Recently, manufacturers are also providing additional functionalities such as self-testing, multiple sensing channels (variable ranges), auto-calibration (no additional references or effort required), fault detection (see next section) and the possibility to program embedded computational resources (to handle new tasks), as now common with field programmable gate-array (FPGA) based chips (Santos and Block, 2012). The fundamental smart sensor architecture is shown in Figure 5.4.

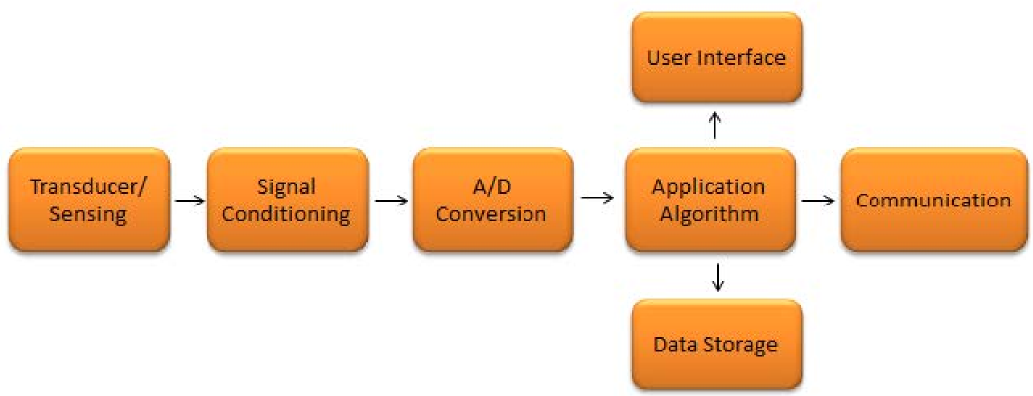

Figure 5.4: General architecture of a smart sensor (Krishnamoorthy, 2005)

5.3 Sensor Issues

Even though the sensor technology has advanced significantly over the years, sensors are inherently noisy. There are uncertainties involved in the measurements and sensor data can also degrade over time. An electrically noisy environment can further corrupt the data. It is important to ensure the integrity of the signal along the transmission path. Using shielded cables and twisted pairs for signal transmission, minimizing the number of components along the path, and standardizing connectors and communication interfaces can help alleviate the noise issues (Ott, 1988). It is desired to get as much accurate and reliable information about the system as possible. Hence real-time sensor data validation and multiple sensor data fusion at a higher level are vital for good system performance. This section will detail some of the most common sensor issues, suggestions on alleviating sensor problems and techniques for sensor data validation and sensor fusion.

5.3.1 Signal Degradation

Sensor signals can degrade due to internal or external factors. The change in characteristics of the primary sensing element causes sensor output to deviate from the ideal behavior. Various factors (environmental sensitivity, handling, over usage etc.) can affect the sensing element or the physics behind the sensing process (Kester, 2010; Ott, 1988).

Faulty sensors, when not detected, can give wrong information about the system status which can be disastrous for system performance and safety. Faulty sensors can cause false alarms and affect system diagnosis. Multiple sensors and sensor-process fault detection and management algorithms can help identifying and dealing with a sensor fault with minimum system interruption.

An external factor responsible for sensor signal degradation is noise. Noise is high frequency variations in the measurement signal over its true value. Signal to Noise Ratio (SNR) is a measure of noise level in the signal. It is expressed in decibels as the ratio of signal power to the noise power. Power is proportional to the square of the amplitude. The focus here should be to have a high SNR, reduce the noise component and maximize the signal. Noise could be added to the signal at different levels. It can originate from the sensing process itself, can be picked up during the signal transmission (electrical noise through EMI in cables), can add at the connection to the measurement device, or during sampling and quantization process.

5.3.2 Noise

To reduce the noise level it is important to understand the sources of noise. Noise can be added at the sensor itself or during

transmission of the sensor signal (Ott, 1988; Norton, 1989; Sheingold, 1972). Noise generated due to sensor components and interfacing circuits is called internal noise. For example, pink noise or $1/f$ noise is due to invariable slow fluctuation of the properties of the materials inside sensors such as fluctuating defect configurations in metal, fluctuating trap density and trap location in semiconductors etc. The power spectral density of pink noise is inversely proportional to the frequency ($1/f$). White noise is a random signal with flat power spectral density meaning the signal contains equal power for any frequency band. In electronics, the white noise component becomes stronger than pink noise above a threshold (corner) frequency. External noise is added in communication wiring during transmission of the sensor signal. The following are some common sources of noise and their characteristics.

- **Electromagnetic Noise (EMI): Electrostatic field due to voltage on an adjacent cable/circuit can cause unintended/parasitic capacitive coupling between the signal line and the adjacent circuitry(Degauque and J.Hamelin, 1993; Paul, 1992). This unwanted capacitive coupling causes noise by developing charges on the signal line. Changing magnetic fields or moving signal lines in a magnetic field can induce noise in the signal line through electro-magnetic induction. Cables carrying alternating current such as power lines adjacent to the signal cable are** a typical source of electro-magnetic noise. The noise level is dependent on the degree of coupling between the source and sensor wiring. In general, the higher the current or closer the sensor circuit to the electrical device, the greater will be the induced noise. This type of noise is minimized by circuit layout and shielding and by keeping the operating bandwidth low.

- Mechanical Noise: Vibration and acceleration effects are also sources of transmitted noise in sensors which otherwise should be immune to them (Webster and Eren, 2016). These effects may alter transfer characteristics (multiplicative noise), or the sensor may generate spurious signals (additive noise). If a sensor incorporates certain mechanical elements, vibration along some axes with a given frequency and amplitude may cause resonant effects. For some sensors, acceleration is a source of noise. For instance, pyroelectric detectors possess piezoelectric properties. The main function of a pyroelectric detector is to respond to thermal radiation. However, such environmental mechanical factors as fast changing air pressure, strong wind, or structural vibrations cause the sensor to respond with output signals which often are indistinguishable from responses to normal stimuli. If this is the case, a differential noise cancellation may be quite efficient.

- Thermal Noise: Electron motion within electrical conductors emit heat (Webster and Eren, 2016). This thermal effect is called ***Johnson*** noise is generated in the resistive component of any circuit impedance by thermal agitation of the electrons. All resistors around the input circuit contribute this. The RMS voltage produced due to thermal noise in frequency bandwidth f (Hertz) is given by the following Johnson noise equation

$$\nu = \sqrt{4kTR\Delta f}$$

Where k is Boltzman's constant (joules per kelvin), R is the resistance and T is the temperature (kelvin). Since the noise depends on temperature, sensitive circuits in potentially hot surroundings are sometimes cooled to reduce the noise level.

- Ground Loops: Ground loops or other types of incorrect grounding cause coupling from output back to input of the circuit via a common impedance in its grounded segment (Ott, 1988). If the resulting feedback sense gives an output component in-phase with the input then positive feedback occurs, and if this overrides the intended negative feedback you will have oscillation. The frequency will depend on the phase contribution of the common impedance, which will normally be inductive and can vary over a wide range.

- Cable Noise: The signal transmission phase is most prone to noise induction (Carlson, Crilly and Rutledge, 2001). Appropriate selection of signal transmission cable is important for reducing noise level. Shielded cables have insulated conductors which are enclosed by a conductive layer (metal foil or conductive polymer shielding). Shielding provides a Faraday cage and reduces noise in signals due to static or non-static electrical fields in the cable environment. It also reduces effect of electro-magnetic induction or electromagnetic radiation from external sources. The shield can be a signal carrier and provide a return path (in coaxial cables) or can be for screening only. Cables with a screening shield are preferred and the shield must be grounded for maximum effectiveness. The cable should be routed such that there is minimum motion or rubbing of cables against each other (or with a surface) to reduce the triboelectric effect.

Other considerations are: sensitive cables such as signal cables may be grouped together, especially in a twisted wire pair to drastically reduces electromagnetic noise; metal cable trays should be implemented with low impedance for the frequencies in use to effectively become a partial screen for the cables with proper grounding; cable shield termination is also a key factor in controlling electromagnetic compatibility but the best practice is often dependent on the particular circumstances. For low frequency applications the shield may be terminated at only one end to mitigate against ground noise currents but this will reduce its effectiveness, particularly against magnetic fields.

For cables carrying low frequency signals, cable terminations have to be designed carefully to avoid coupling with noise currents fl owing in the ground. If the sensor is not directly connected to ground as in Figure 5.5(a) above it may be possible to terminate the screen at both ends, thus providing maximum protection against inductively coupled disturbances. If the sensor is grounded as in Figure 5.5(b), the voltage drop across the ground impedance to noise currents in the ground will give rise to high currents in the shield and noise voltages may be present at the input to the amplifier. This can be overcome as shown by terminating the cable at one end only, thus avoiding the ground loop, but the performance of the shield may be reduced. If high performance is required under all conditions, e.g., with the sensor grounded it may be necessary to introduce transformer coupling or opt-isolation in order to minimize unwanted coupling (Carlson, Crilly and Rutledge, 2001).

The above mentioned noise sources are induced during the signal transmission. Noise/errors are also induced at the measurement device during acquisition of analog signals and their conversion to digital form.

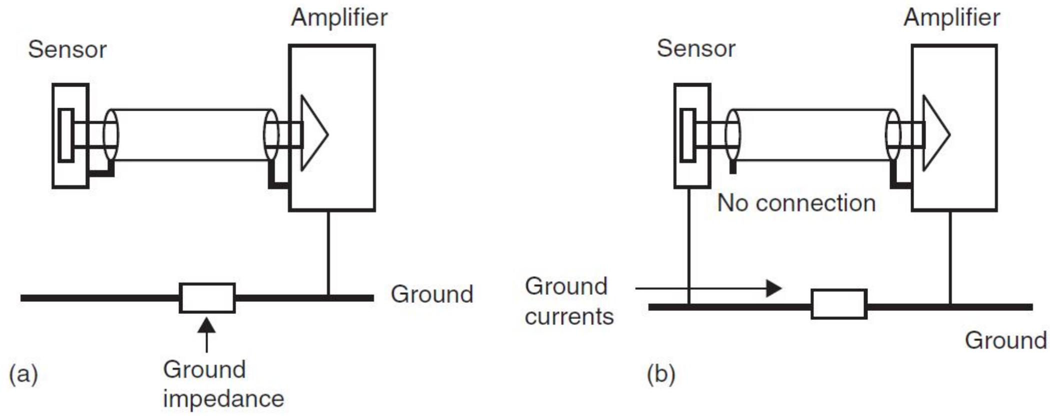

Figure 5.5: Screened cable termination methods (a) Sensor not grounded; (b) Sensor grounded (Bensky, 2004).

5.3.3 Noise Reduction Techniques

Noise can get added at different levels in the signal flow path. Many techniques are recommended to reduce the noise level. These include using best practices for sensing, signal transmission and measurement to control unwanted noise induction and software techniques to reduce/eliminate noise components from the acquired signal (Ott, 1988).

- **Appropriate Measuring Configuration: Appropriate type of the sensor signal and measuring configuration can avoid unwanted noise in the measurement signal (Webster and Eren, 2016; Carlson, Crilly and Rutledge, 2001). The sensor signal can be differential, Referenced Single Ended (RSE) or Non-Referenced Single Ended (NRSE). In the differential configuration, each** channel of the signal has a separate negative and positive leads connected to the DAQ module. The DAQ measures potential difference between two leads directly thus rejecting common mode voltage. A differential signal can be measured accurately since the absolute ground potential does not affect the measurement value. A referenced single ended measurement system measures voltage with respect to the ground pin - directly connected to the measurement system's ground. The sensor ground should be the same as the measurement device's ground to avoid ground loops. In a non-referenced single ended system, all measurements are made with respect to a single node which is not grounded. Hence, a single channel NRSE system is the same as a single channel differential measurement system. The single-ended configurations are susceptible to ground loops, often showing noise corresponding to the alternating voltage difference between two grounds (source and measurement system).

- Electromagnetic Noise Reduction: Electromagnetic induction due to changing magnetic flux surrounding the signal cable is a common source of noise (Ott, 1988). A changing magnetic flux can be a result of an alternating current carrying line (say a power line) running adjacent to the signal cable or a moving signal cable cutting the magnetic field lines. Using twisted pair of wires for transmitting the signal dramatically reduces electromagnetic noise. A tightly twisted pair of wires reduces the loop size (flux area). Moreover, two consecutive loops formed due to twisting induce current in opposite directions in each wire thus cancelling them out. Isolation techniques are used to separate signals from each other and from other circuitry in the system. A high voltage carrying signal source can damage the surrounding system circuitry and vice versa, a sensitive signal can pick up noise from the adjacent circuitry if not properly isolated. Common types of amplifiers use magnetic, optical, or capacitive means to couple the signals.

- Signal Processing Techniques: Proper signal acquisition and further processing of raw signals can eliminate the majority of the noise introduced during signal transmission (Smith, 2013). The measurement frequency should be within the sensor's bandwidth or dynamic range. The sampling rate must be high enough; 4 to 8 times the highest frequency component expected in the signal being measured to prevent aliasing. The Nyquist rate is twice the maximum component of frequency in the signal and is the minimum sampling rate required to reconstruct the signal.

Noise filtering can be done in hardware or software but should filter noise close to the noise source and before any further signal processing or interpretation. Filters are classified based on the signal frequency the filter is designed to allow or eliminate. For example, low pass filters allow frequencies lower than the corner frequency F_c and block higher frequency signals. A high pass filter will allow signals with higher frequency components while rejecting DC and lower frequency signals. Band-pass filters allow frequencies between F_L (lower limit) and F_H (higher limit) and block all other frequency signals. A band-stop filter is opposite of the band pass filter and it allows signals lower than F_L and higher than F_H.

5.4 Sensor Data Validation

In practice, physical sensing devices usually do not operate in accordance with their theoretical models due to various factors as described in the previous chapter. Sensor measurements have an element of uncertainty in them because various sources add noise to the readings or cause a malfunction of the sensor altogether. Individual sensors operating alone cannot present a complete picture of the whole actuator environment and must be used in concert with other sensors in the architecture for a more realistic assessment of the actuator capabilities. Hence, there is a need to improve the status of sensors from a technology with limited analytic abilities to one with more complete analytical resources. The development

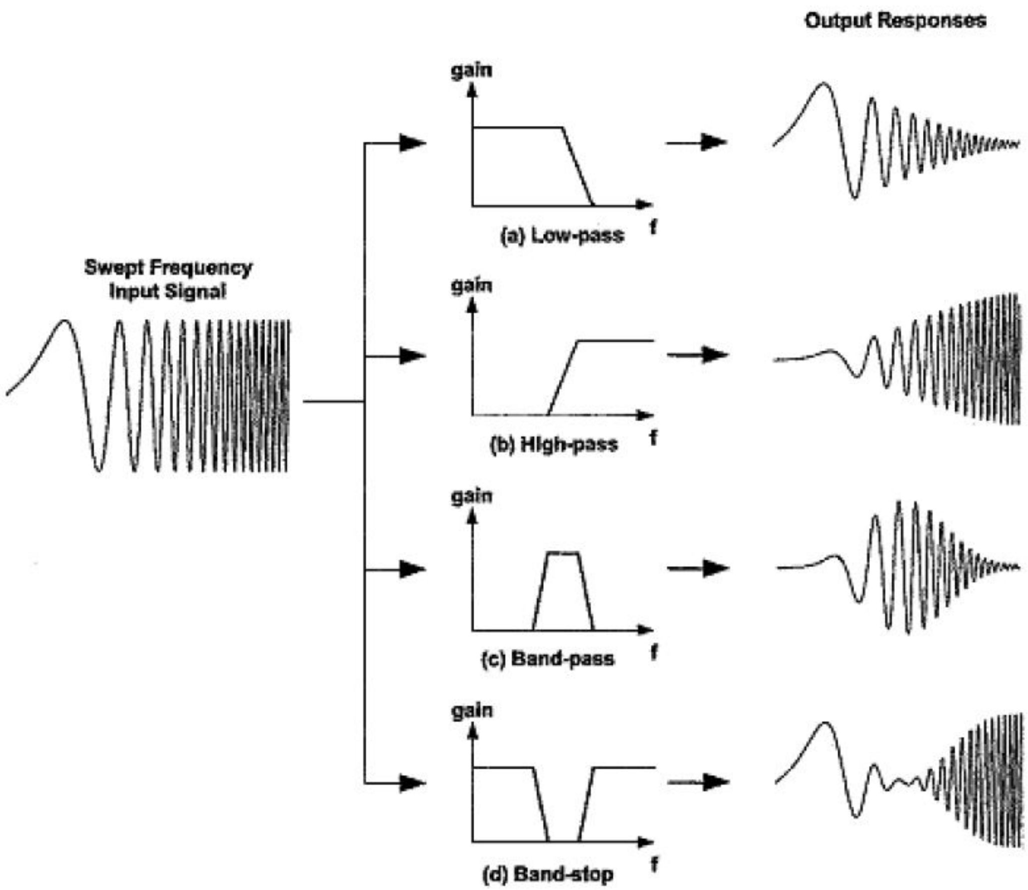

Figure 5.6: Filter types and responses (Nat, 2004)

of smart sensors is an initial step in this process. This must be bolstered by the development of computer-based tools that employ validation and fusion methods to combine information from dissimilar sensors to estimate the operating status of the actuator and provides intelligent support to diagnosis.

Some form of safeguard is needed to protect against the failure of any sensor in the architecture. The traditional approach to

operational fault tolerance has been one of fault prevention through over design to remove possible causes of failure. In the simplest version, this takes the form of physical redundancy using multiple sensors. However, in some cases, due to the sensor size, cost and the increased complexity of the system, this scheme may not be applicable. This results in systems that are not optimal with respect to factors like weight, compactness, cost etc.

A more modern approach is to create an architecture that includes redundant analytical capabilities to minimize/counteract failures by forming functional or inferential sensors (Brignell and White, 1996). Inferential sensors replace the physical redundancy with analytical redundancy by taking data obtained from a particular sensor and inferring quantities other than its primary measurand by means of some mathematical models or other similar techniques (Khaleghi et al., 2013; Xing and Xia, 2016). The effectiveness of such techniques has been demonstrated to provide joint position sensor fault tolerance using accelerometers and joint torque sensors; instead of redundant position sensors. Such techniques not only provide alternative pathways for information flow in case of sensor failures but also greater confidence in the measured data. However, fusion itself is not a substitution for a good data. It is obvious that the benefits of fusion cannot be achieved if the input data is of bad quality. Hence validation is necessary to prevent the propagation of

erroneous data. These objectives can be achieved by implementation of the algorithms necessary to perform the above tasks, within the embedded sensor module. The objective of this chapter is to provide an overview on the guiding principles, the associated terminology, architectures and techniques of sensor validation and fusion.

Noise reduction techniques and signal conditioning improve accuracy of the measured data. In many critical applications, just the standard noise reduction methods are not sufficient. It is important to detect abnormal behavior of the sensor itself. Faulty sensor data can result in catastrophic failure of the system. It is essential to validate sensor data and have a *confidence value* associated with each measurement. Sensor data validation is a technique that evaluates measured data and flags uncertain or improbable data to avoid their usage (Webster and Eren, 2016). Sensor data validation techniques use system characteristics, mathematical models and previous data history to predict new value of the measurement. A *quality index* is assigned to the actual measurement based on its closeness/agreement with the predicted value. Reconciliation methods correct inaccurate measurements and provide reconstructed signals for degrading sensors.

Some common validation techniques include checking measured values to lie within the system expected range and flag outlier readings (Khaleghi et al., 2013). Maximum change and rate of change of sensor data can also be used to diagnose sensor degradation and failure. For sensors whose characteristics can be captured by a model, estimation techniques such as Kalman filtering can be used to predict an interval within which the sensor measurement would lie (Khaleghi et al., 2013; Xing and Xia, 2016). In case of multiple sensors, physical or analytical redundancy can be used to validate sensor data (majority voting scheme) or reconstruct lost data (Xing and Xia, 2016; Wang and Qin, 2016). Complete failure of the sensors is relatively easy to identify, but it is imperative to detect degrading sensor signals and incipient sensor failures to take timely actions. This is done by temporal analysis of the sensor data at regular intervals to check for sensor bias, drift and need for recalibration (Denton, 2010). Transient system behavior should not be confused with degrading or drift in sensor signals.

It is crucial to distinguish between a faulty sensor and a faulty system. For example, if a sensor reading is 20% higher than the predicted value, the challenge is to determine whether the reading indicates a possible system problem or it is the sensor itself which has drifted out of calibration. This is the principal goal of a sensor process fault management system. Sensor redundancy (physical or analytical) and data from multiple sensors (sensor fusion) can be used to identify and distinguish incipient sensor or system faults.

5.5 Sensor Fusion

The argument for using multiple sensors in all the existing mechanical systems is presented in Chapter 1 and Chapter 2. These sensors would generate huge amount of data that need to be evaluated and integrated. It becomes difficult for a system level controller to analyze data from each individual sensor to make a decision. Moreover, a single sensor may not cover the entire operating regime or it may have limited spatial and temporal coverage given the scope of the entire system. Sensor fusion is a technique of merging/integrating data from two or more sensors to obtain meaningful information (hopefully more accurate and reliable than using individual sensors) about the system state. The information combined from multiple sensors is presented in a simpler and coherent structure to ease in the decision making process.

Design and implementation of a sensor fusion algorithm is not a trivial task. It includes selection of appropriate sensors, sensor modeling, interpretation of diverse sensor data, and fusion processing. Sensor data can be incomplete, imprecise, and inconsistent with other sensors. Moreover, sensor data can get corrupted during the transmission or the sensor itself may degrade over time. Different sensors can have different working principles. The output data may have different units (position, velocity or acceleration) and different sampling frequency.

A sensor fusion algorithm should carefully integrate data from multiple sources, taking the above mentioned factors into consideration, to achieve best possible estimate of the actual system state. A poorly designed fusion approach can result in the final value worse than the best sensor in the system. Outputs from all the sensors to be fused must be converted into a common representation/data structure. Consistency should be checked among data from multiple sensors before integrating them. One method is to compute the Mahalanobis distance between two sensor measurements (Jo et al., 2017). It is a unitless measure to evaluate similarities between two sample sets and is defined as

$$T = \sqrt{(X_1 - X_2)\, C^{-1}\, (X_1 - X_2)}$$

where X_1 and X_2 are two sensor readings and C is co-variance related to two sensors. The Mahalanobis distance differs from Euclidian distance in a sense that it takes into account the correlation between data sets and it is scale-invariant. The lower the distance, the more consistent are the two sensor readings.

In addition to checking consistency among sensors, it is important to assess uncertainty of each sensor reading (confidence value) and propagate the uncertainty in the fusion process. Uncertainty can be characterized by probabilities and belief functions. Uncertainty in sensor data is typically modeled as a Gaussian distribution.

Each sensor reading/signal can be assigned a probability from 0 to 1 or it can be viewed as a membership function of a fuzzy set. The center of a symmetric distribution (Gaussian or ellipsoid) is the mean of the measurement and the uncertainty can be indicated by one standard deviation from the mean.

Recent advancements in computational hardware and their availability at low cost have made sensor fusion possible in real-time (Tesar, 2016*a*; Webster and Eren, 2016). Combining data from multiple sensors has significant advantages than using a single sensor (Liggins, Hall and Llinas, 2017). This approach provides a better estimate of the actual physical state of the system by reducing overall uncertainty of sensor data, resulting in increased accuracy of the final output. Multiple sensors can be used to validate the results (readings, output) of each other and provide redundant information, which increases robustness and operational reliability of the system in case of a sensor failure. This increases total availability of the system by reducing risk associated with single point failures. Additionally, fusion algorithms can reduce noise in sensor data as the signal components from multiple sensors are highly correlated whereas noise measurements are random.

One of the side advantages of fusing data from multiple sensors is that it requires sensor data to be represented in a standard format (Liggins, Hall and Llinas, 2017). Data from sensors belonging to the

same sub-system can be combined at a local level controller and only useful information is passed on to the system level controller in a standard representation. This allows flexibility in the system with control software becoming more or less independent of the hardware. Sensors based on different working principles and measurement attributes (sampling frequency, output type etc.) can be used without changing the control software. Similarly it is possible to re-design control algorithms without regard to physical sensor types. Thus it improves overall information flow and allows modularity in the system.

Many mathematical techniques exist for fusing data from multiple sensors (Khaleghi et al., 2013; Jo et al., 2017; Hassen, 2015; Liggins, Hall and Llinas, 2017). It can be a simple averaging of readings obtained from multiple sensors or a probabilistic approach like Bayesian inference or a least square method like Kalman filtering or modern intelligent approaches using fuzzy logic, neural networks or genetic algorithms. An overview of some of the common techniques is presented in the following sections.

5.5.1 Weighted Averaging

In one of the simplest methods, combining data from multiple sensors can just mean taking an average of readings from the sensors. This method would work well if all the sensors have similar accuracy

and are operating perfectly. If one of the sensor goes off (produces bias or drift in the measurements or complete failure) then a simply averaged output can be severely off. A variation of simple averaging is weighted averaging where along with the measurement; quality or confidence in the measurement/reading is also considered in the final estimated value. If Z_i is the reading from the i^{th} sensor in an n sensor system, the weighted average is given by

$$Z = \sum_i w_i \cdot Z_i$$

where

$$\sum_i w_i = 1$$

Weights can be constant or changing based on the sensor performance and operating regime. In probabilistic terms, sensor output can be viewed as a Gaussian distribution with sensor reading as the mean value and uncertainty in the measurement captured in standard deviation of the distribution. Weight can be inversely proportional to the standard deviation (or directly proportional to the accuracy of the sensor). Sensor data validation algorithm also assigns a confidence value to each sensor reading. The normalized confidence value of each sensor reading can also be chosen as the weight in the fusion process.

5.5.2 Kalman Filtering

Kalman filter is an inference algorithm for linear dynamical systems where variable uncertainties have a Gaussian distribution (Welch and Bishop, 2004). If the sensor can be modeled as a linear system, the Kalman filter provides optimal estimates for fused data. This filter is one of the most commonly used data fusion algorithms today typically in global positioning system, inertial navigation unit etc. due to its small computational requirements and simple recursive estimation of states (Hassen, 2015; Liggins, Hall and Llinas, 2017; Drolet, Michaud and Cote, 2000; Wang and Qin, 2016; Xing and Xia, 2016).

There are two main steps in Kalman filter algorithm: time update and measurement update. In the time update, previous system state and control input are used in a linear model to get *a priori* estimate of the new current state and error covariance. The measurement update step incorporates a new measurement of current state into the *priori* estimate to obtain an improved post-*priori* estimate. The Kalman filter algorithm assumes the following linear model for the system and measurement

$$x_t = Ax_{t-1} + Bu_{t-1} + w_t$$

$$z_t = Hx_t + v_t$$

The first equation is the system dynamic model where,

x_t **is the state vector containing variables of interest for the system at time** t

A **is the state transition matrix (non-singular)**

u_t **is the vector containing control inputs**

B **is the control input matrix applying effect of inputs to the state parameters**

w_t **is system noise modeled as zero mean multivariate normal distribution with covariance matrix** Q**.**

The second equation is sensor model - noisy observation of the system where,

z_t **is the vector of measurements at time** t

H **is the transformation matrix mapping internal states to measurement space**

v_t **is a vector of measurement noise modeled as zero mean multivariate Gaussian distribution with covariance matrix** R**.**

The state transition matrix, control input matrix and measurement transformation matrix are constant in most cases but they can be functions of time (A_t, B_t, H_t)**.**

The first step is the prediction step to compute an *a priori* estimate $\hat{x}_{t|t-1}$ **of the state** x_t **from previous state** $\bar{x}_{t-1}$ **and control input** u_{t-1}

$$\hat{x}_{t|t-1} = A\bar{x}_{t-1} + Bu_{t-1}$$

$$P_{t|t-1} = AP_{t-1|t-1}A^T + Q$$

where $P_{t|t-1}$ **is the variance associated with prediction step for yet unknown state** $\bar{x}_t$**.** $P_{t-1|t-1}$ **is the final covariance matrix of the previous state** $\bar{x}_{t-1}$**.**

The second step is the measurement update to compute a posterior (and final) estimate of state $\bar{x}_t$ **from the *a priori* estimate** $\hat{x}_{t|t-1}$

$$\bar{x}_t = \hat{x}_{t|t-1} + K_t(z_t - H\hat{x}_{t|t-1})$$

$$P_{t|t} = P_{t|t-1} - K_t H P_{t|t-1}$$

K_t **is Kalman gain and** $P_{t|t}$ **is the covariance matrix for final state estimation** $\bar{x}_t$ **to be used in the next step. It is a recursive algorithm and the process repeats with** $t = t + 1$**. The algorithm is initialized with the estimated initial system state** $\bar{x}_0$ **and covariance of the initial estimate** $P_{0|0}$**. Once the algorithm is initialized, each step is a simple**

algebraic computation making the Kalman filter well suited for real-time applications.

A simple one dimensional Kalman filter to integrate (fuse) data from two sensors is demonstrated in (Drolet, Michaud and Cote, 2000). Sensor output can be modeled as a Gaussian Probability Density Function (PDF) with the sensor reading as the mean value (μ) and amount of uncertainty/noise indicated by the standard deviation (σ) or variance (σ^2) (Vargas-Melendez et al., 2017). If μ_1, σ_1 and μ_2, σ_2 are the sensor readings and the standard deviations for two sensors, their Gaussian distributions are given by the following equations

$$y_1(r, \mu_1, \sigma_1) \equiv \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(r-\mu_1)^2}{2\sigma_1^2}}$$

$$y_2(r, \mu_2, \sigma_2) \equiv \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(r-\mu_2)^2}{2\sigma_2^2}}$$

The information from two sensors can be fused by multiplying their Gaussian functions to give an estimate of the actual system state. A key property of the Gaussian function is that the product of two Gaussian functions is another Gaussian function.

$$y_{fused}(r, \mu_1, \sigma_1, \mu_2, \sigma_2) \equiv \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(r-\mu_1)^2}{2\sigma_1^2}} \times \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(r-\mu_1)\times^2}{2\sigma_2^2}}$$

$$= \frac{1}{\sqrt{2\pi\sigma_1^2\sigma_2^2}} e^{-(\frac{(r-\mu_1)^2}{2\sigma_1^2} + \frac{(r-\mu_1)^2}{2\sigma_2^2})}$$

Simplifying the above equation, to get

$$y_{fused}(r, \mu_1, \sigma_1, \mu_2, \sigma_2) = \frac{1}{\sqrt{2\pi\sigma_{fused}^2}} e^{-\frac{(r-\mu_{fused})^2}{2\sigma_{fused}^2}}$$

where

$$\mu_{fused} = \frac{\mu_1\sigma_2^2 + \mu_2\sigma_1^2}{\sigma_1^2 + \sigma_2^2} = \mu_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}(\mu_2 - \mu_1)$$

$$\mu_{fused}^2 = \frac{\sigma_1^2\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

Thus the result of the Kalman filter can be expressed as the weighted average where weights are optimally calculated to minimize the squared error.

$$\mu_{fused} = w_1 * \mu_1 + w_2 * \mu_2$$

$$\mu_{fused} = \left[\frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}\right] * \mu_1 + \left[\frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}\right] * \mu_2$$

$$\frac{1}{\sigma_{fused}^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}$$

Since the variance of the estimate is less than that of either sensor, it increases the confidence in the value thus obtained.

5.5.3 Bayesian Networks

Bayesian networks are a powerful graphical tool to combine information from different sources in a probabilistic form. Bayesian networks are graphical modeling tools comprising of probabilistic graphical models to represent a set of (random) variables and their

conditional dependencies via a directed acyclic graph. These concepts are derived from graph theory, probability theory, and statistics and provide a method for both modeling of complex problems (incorporating uncertain knowledge) as well as for decision making (performing reasoning) under uncertainty (Pearl, 1988; Subrahmanya, Shin and Meckl, 2010).

A Bayesian network represents the interconnectedness between the different random variables that represent the parameters of interest in a given domain (Koch, 2016). The focus in this work are the parameters and multibody system and their relationships described in Chapters 2 and 3. The graphical framework of Bayesian networks provides an intuitive understanding of the domain being modeled and allows for a compact representation of multivariate probability distributions (by representing the joint probability as product of local distributions).

In a Bayesian network representation of a system, illustrated in Figure 5.7, the nodes can represent the physical variables pertinent to the system and its components. The links between any pair of nodes represent the relationship between the different variables. Thus, these links are defined here as a *process* that converts the physical parameter represented by a parent node into the parameter represented by its child node. For discrete variables, the strength of this correlation is quantified by the conditional probability table

(CPT) of the child node.

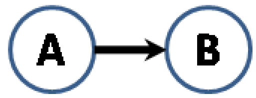

Figure 5.7: Example Bayesian network with two nodes

5.5.4 Bayesian Inferencing

In Bayesian inference, the probability estimate of the system state (hypothesis) is updated as additional sensor data (evidence) is measured (Koch, 2016; Liggins, Hall and Llinas, 2017). The information from each sensor is represented as a probability density function or probability values. Bayes' rule is central to computing the posterior probability of the system state given data from multiple sensors and is given by

$$p(H|E) = \frac{p(E|H)p(H)}{p(E)}$$

where H stands for any hypothesis, $p(H)$ is the *a priori* probability of hypothesis H being true (before event E is observed). Here, $p(H|E)$ is the posterior or updated probability of hypothesis H after event E (sensor measurement) is observed. $p(E|H)$ is known as the "likelihood". It is the probability of occurrence of event E (getting sensor data) given H is true. It is usually determined based on past experimental results. Thus Bayesian inference provides fused information from multiple sensors or estimated value of the state

given measurements from multiple sensors. Priory probabilities are dependent on the sensor physical characteristics and can be determined from sensor specifications (accuracy, sensitivity etc.) and previous experimental results. The left hand side of the equation is the desired estimated value of the state given measurements from multiple sensors. A comprehensive methodology for utilizing data from multiple sensors using Bayesian Networks is discussed in (Krishnamoorthy, 2010).

Although the inclusion of sensors in a system provides many advantages, a multi-sensor system has to deal with challenges such as physical integration of sensors with the existing system, cabling complexities, sensor noise, communication, data management, maintenance, and integration cost etc. The chapter discussed best practices to alleviate complexities in a multi-sensor system. Individual sensors cannot be relied upon as each sensor is also a potential single point failure. Sensor fusion techniques are used to combine data from multiple sensors and represent useful information to the controller. A multi-sensor system can take advantage of structured decision making theory (Krishnamoorthy, Ashok and Tesar, 2015) and Bayesian network based sensor and process fault management technique (Ashok, Krishnamoorthy and Tesar, 2011) to improve fault tolerance and overall performance of the system.

5.6 Fault Detection & Isolation

A *sensor fault* is a disparity between the ideal value that a sensor is expected to output under specified operating conditions and the actual value outputted. This disparity does not necessarily indicate sensor flawed. Possible causes are a temporary drift, bias or unexpected higher level noise in the reading. Hence, the sensor output needs to be tracked over multiple sampling instants to determine with certainty that the sensor itself is faulty. Good references are (Krishnamoorthy, 2010; Krishnamoorthy, Ashok and Tesar, 2015).

Chapter 6

Distributed & Self-Organizing Wireless Networks

For most engineering applications, Bayesian network nodes represent the physical parameters of interest for sensors integrated into a dynamic system. A network composed of these measurands/variables needs to be designed model the actual system as closely as possible since it is meant to represent the system behavior for decision-making during operation. The process tends to be iterative, as there are numerous design criteria that need to be balanced simultaneously.

The information feeding such a decision logic structure derives from a communication network that operates effectively under the required environment and user specifications.

6.1 Communication

An important consideration for a multi-sensor architecture in tractor trucks is connecting sensors to a central or embedded (local) processor or controller in each trailer and relaying processed information to the central controller or other remote nodes (a monitoring group at headquarters).

Modern sensor outputs are almost entirely electrical characteristics that are produced by the sensor alone or by its integrated excitation circuit and signal conditioner. These characteristics can include voltage, current, charge, frequency, amplitude, phase, polarity, shape of a signal, time delay, and digital code (Smith, 2013; Halsall, 1996).

The most popular digital communication between an integrated sensor and peripheral device is a serial link (Yang, 2017; Iyengar and Brooks, 2016). As the name implies, a serial link sends and receives bytes of information in a serial fashion, one bit at a time. These bytes are transmitted using either a binary format or a text (ASCII) format. For communicating an integrated sensor with a digital output format, the most popular formats are PWM (pulse-width modulation) and I^2C and its variations. The I^2C (pronounced I-squared-C) protocol was developed by Philips Semiconductors for sending data between the I^2C devices over two wires. It sends information from a sensor to a peripheral device serially using two lines: one line for data (SDA) and one for clock (SCL) to synchronize communication. The protocol is based on a concept of the master and slave devices. A master device is a controller (microcontroller) that is in charge of the communication bus at the present time and controls the clock.

The Controller Area Network (CAN) standard was originally developed within the automotive industry to replace the complex electrical wiring harness with a two-wire data bus (Iyengar and Brooks, 2016; Goswami et al., 2012). This wired communication technology seamlessly integrates components with an onboard monitoring system. It is now widely used in other industries such as aerospace, automation, etc. The specification allows signaling rates up to 1 MB/s, high immunity from electrical interference (twisted pair shielded cables), and an ability to self-diagnose and repair errors. It is now widespread in many sectors, including factory automation, medical, marine, aerospace and of course automotive. It is particularly suited to applications requiring many short messages in a short period of time with high reliability in noisy operating environments.

Nodes (communication interfaces) can be added or removed at any time, even while the network is operating (hotplug) (Iyengar and Brooks, 2016; Safak, 2014). Unpowered nodes should not disturb the network bus (network channel), so transceivers should be configured so that their pins are in a high impedance state with the power off. The standard specification allows a maximum cable length of 40 m with up to 30 nodes.

The Universal Serial Bus (USB) is a cable bus that supports data exchange between a host computer and a wide range of simultaneously accessible peripherals (Iyengar and Brooks, 2016). The attached peripherals share USB bandwidth through a host scheduled, token-based protocol. The bus allows peripherals to be attached, configured, used, and detached while the host and other peripherals are in operation. There is only one host in any USB system. The USB interface to the host computer system is referred to as the Host Controller, which may be implemented in a combination of hardware, firmware, or software. USB devices are either hubs, which act as wiring concentrators and provide additional attachment points to the bus, or system functions such as mice, storage devices or data sources or outputs. A root hub is integrated within the host system to provide one or more attachment points.

Ethernet is a well established specification for serial data transmission (Carlson, Crilly and Rutledge, 2001). In 1985 Ethernet was standardized in IEEE 802.3, since when it has been extended a number of times with Gigabit Ethernet at 1 Gbit/s being introduced in 1999.

6.1.1 Wireless Communication Link

In the past two decades, advances in integrated circuit miniaturization and logic circuit speed have resulted in reliable low-cost wireless communication devices that connect or interface with essentially all modern electronics (Goswami et al., 2012). WLAN, WiFi, Bluetooth and ZigBee have become standards for practically all industry and commercial applications (Bensky, 2004; Santos and Block, 2012).

Currently, the most commonly used wireless technologies are ZigBee (based on IEEE 802.15.4) and WiFi (based on IEEE 802.11b/g standard). ZigBee is a communication protocol that is defined by the ZigBee Alliance (http://www.zigbee.org). It uses IEEE 802.15.4 as a foundation establishing individual wireless links and extends upon it to provide routing, application support, security, etc.

WiFi is the generic name associated with products that utilize the IEEE 802.11 specification. WiFi Alliance (http://www.wi-fi.org/) is the group responsible for evaluating a product and then branding it as WiFi-capable.

IEEE 802.11 is the standard followed to deploy Wireless Local Area Networks (WLAN) in the 2.4, 3.6 and 5 GHz frequency bands (Molisch et al., 2004). Over the years, IEEE 802.11 has evolved into a family of standards. It now consists of protocols from IEEE 802.11a to IEEE 802.11n, with new additions continuing to be developed. Several different characteristics like data rate, bandwidth, communication range, etc., differ between the various 802.11 protocols.

The data rate for IEEE 802.11 standard varies from 1 Mbps (Million bits per second) to now over 1Gbps, or over 1000Mbps, in IEEE 802.11ac. The bandwidth of channels in the IEEE 802.11 spectrum is 20 MHz or 40 MHz wide, depending on the protocol being used. The range of communication possible using IEEE 802.11 varies from 100 meters to over 1000 meters in outdoor environments, depending on the protocol being used. The IEEE 802.11 offers a higher data rate and range as compared to IEEE 802.15.4 meaning higher control capability due to greater sensing and feedback but at a higher cost.

The operational frequency bands of IEEE 802.15.4 operation are 868 868.6 MHz, 902 928 MHz and 2.4 2.4835 GHz (Molisch et al., 2004). The maximum channel data rates for data communication specified by IEEE 802.15.4 are of 250 kbps at 2.4 GHz, 40 kbps at 915 MHz and 20 kbps at 868 MHz. The corresponding channels allocated are 1 channel in the 868 868.6 MHz band, 10 channels in 902 928 MHz band and 16 channels in 2.4 2.4835 GHz. It is designed for short-range communication with ranges up to 100 feet, ideal for local communication.

ZigBee has been extensively used in home automation (Callaway et al. 2002), embedded sensing, industrial control etc. Zigbee is the name of a standards-based wireless network technology that addresses remote monitoring and control applications. In wireless sensor networking, available technologies like MEMSIC MICAz, TelosB, Iris, etc. all use ZigBee as the communication protocol. An overview of IEEE 802.15.4 and ZigBee can be found in (Rakshit, et al. 2012). ZigBee is a low-power simple protocol with typically the lowest cost to setup.

Bluetooth is an example of a wireless personal area network (WPAN), as opposed to a wireless local area network (WLAN) (Iyengar and Brooks, 2016). It is based on the creation of *ad hoc*, or temporary, on-the-fly connections between digital devices associated with an individual person and located in the vicinity of around ten meters from him. Bluetooth devices in a network have the function of a master or a slave, and all communication is between a master and one or more slaves, never directly between slaves. The basic Bluetooth network is called a *piconet.* It has one master and from one to seven slaves. A scatternet is an interrelated network of piconets where any member of a piconet may also belong to an adjacent piconet. Thus, conceptually, a Bluetooth network is infinitely expandable, although a device may be a master in one piconet only.

Bluetooth operates at data transfer speed of 1 MBPS, much greater than ZigBee but is still no as common and easy to implement in industrial applications.

While the advantage of a wireless versus wired LAN is obvious, there are still three primary disadvantages to wireless networks as compared to wired: range limitation, susceptibility to electromagnetic interference (EMI), and security (Iyengar and Brooks, 2016; Monks et al., 2016). While the first two issues are practical concerns, security is becoming the dominant issue, especially with intellectual property is involved (transmitting valuable data or implementing/operating a proprietary scheme). Range capabilities is dependent on the network system implemented and EMI prevention has been discussed in Chapter 3 and 5. Wireless communication security is a large and constantly evolving field, due to the high rate of new technology obsoleting older. This topic is briefly detailed at the end of the Communication section.

6.1.2 Implementing Communication

The selected network topology and communication protocol on a truck trailer should reduce cable complication or eliminate if feasible and make information flow efficient to reduce overall power consumption. Connecting all onboard sensors individually to a central processor would require many cables and increase the cable lengths. Other than cabling complexity, long running cables carrying analog signals are susceptible to signal degradation. Additionally, such an arrangement (Star to point topology, centralized) increases computational load on the central processor (Bensky, 2004).

A computer program that simply executes a (logic) loop indefinitely has a limited practical application. In most microcontroller systems (especially for industrial use) the primary focus should be to be able to interrupt the normal sequence of program flow to alert the microprocessor to the need to do something. This is achieved with a signal known as an *interrupt*.

If the network is centralized as mentioned above, more interrupts are needed to manage all the sensors individually, resulting in more power consumption (greater "switching" power) and greater demand on the overall system logic (controller scheme). Because of this, the sensor network should be as distributed as possible (decentralized), by grouping sensors in a sub-system and a low power local processing unit dedicated to each sub-system.

In the previous sensor example, a bearing system is being monitored by an accelerometer, a microphone and a temperature sensor. Accelerometer and microphone measurements are sampled at a (~50 kHz) rate. It is inefficient to sample at such a high rate from the central processor, which has to deal with multiple bearings per vehicle (possibly multiple vehicle bodies) and other onboard sensors. A better practice is to use a (microcontroller-based) local or sub-system on the bearing system with digital I/O (input/output) and ADC.

The microcontroller sub-system (commercially available at ~ $1.50 in volume) can be connected to all of the mentioned network protocols to send information to a controller or processor (Tesar, 2011, 2012). This sub-system handles raw data coming from all three bearing sensors and performs necessary signal processing (ADC/DSP), and classifies any potential bearing defects. Only the results of the classification of possible defects and the alarms for impending defects should be transmitted to high level controllers.

To further reduce the power consumption, network modules (transceivers) typically have various power saving operation modes typically comprising of a scheme based on standby mode and transmit only at an specified times or conditions.

Essentially, a multi-sensor system should be comprised of modular components distributed throughout a tractor truck system (a trailer or a wheel diagnostic subsystem) and be able to send information to a central controller about individual component states and that of sub-components over a network. Each component should have a unique identification in the local tractor truck network. The wireless link information is received on a central controller computer which can be running a visualization software to display the state of the critical components to the driver or out of vehicle (remote) operator/supervisor. With this, the driver is always aware of the truck condition in near real-time and can make informed and timely decisions with a sophisticated controller software. Alarms are triggered for any impending faults and performance data can be reported to a web server over the internet to get access from a remote monitoring facility. Chapter 8 details more on potential applications.

6.1.3 Smart Truck Communication

Conventional active safety systems for Articulated Heavy Vehicles (AHVs) are based on wired networks connecting sensors, controllers, actuators, power-packs, etc. mounted on different vehicle units. Such wiring systems require that multiple vehicle units be connected through a large number of cables and sockets. While deploying such a large amount of wiring in a single-unit vehicle is straightforward, it becomes quite difficult to handle and manage in a multi-unit vehicle, such as an AHV with a tractor and multiple trailers. Each time the tractor switches its trailers, the driver needs to properly reconnect or switch cables. Furthermore, articulation angles between adjacent vehicle units are continuously varying, which increase the probability of disconnection or damage in the connecting wires/sockets. Alternatively, wireless communication equipment can be embedded in an AHV to connect different units through wireless links. Adopting a wireless communication has several advantages, e.g., flexibility, cost efficiency, ease of maintenance, road safety enhancement, connectivity with neighboring vehicles, and traffic reduction. With a wireless communication system, there will be no ports or physical connections between the vehi-

cle units. Some applications, e.g., anti-lock braking systems (ABS), on heavy vehicles have been implemented with a networking protocol named controller area network bus (CAN-bus) for real-time communication. Replacing CAN-bus with a wireless network will decrease the cost, installation complexity, and weight of wiring.

On the other hand, utilizing a shared wireless network results in new challenges. A conventional control system generally involves multiple dynamical systems, which are linked through ideal channels. However, wireless communication is often implemented under the condition of transmitting data through imperfect channels that are band-limited and delayed. Network Control Systems (NCSs) were born to close controller loops over a wireless network (Zhang, Han and Yu, 2016). NCSs are distributed systems, in which the communication among sensors, actuators and controllers is implemented through a shared network. The goal of introducing a wireless NCS into an active safety system for AHVs is to produce proper inputs for each controller to ensure the stability of the overall dynamic system.

Latency is defined as the time used for a receiver to successfully receive a message from a transmitter (Smith, 2013; Halsall, 1996; Carlson, Crilly and Rutledge, 2001). Delay can occur in state measurement and control actuation. Pack-loss, where data packs or packets (data units being transferred or communicated) have been

lost in transmission, generally occurs due to transmission errors in physical networks links or buffer over-flows in congestion case. Long delays is one of the causes of packet reordering, and consequently results in packet-loss when the receiver discard the outdated arrivals. Interpreting the network as a communication channel with time varying delay is one of the simplest ways to hide the system complexity.

Presently, the automotive industry is producing intelligent vehicles to reduce traffic, pollution, and fatal accidents around the world. These achievements add more complexity and require larger amounts of processing power and communication hardware to exchange data inside each vehicle and among neighboring vehicles. Typically, vehicles usually include hundreds of sensors and numerous Electronic Control Units (ECUs) that communicate over a shared network (Tesar, 2012). The goal of such structures is to produce proper input for each controller to ensure the high performance of the overall dynamic system. A list of new approaches in different areas of NCS like estimation, analysis, and controller synthesis for packet-rates, sampling, delays and dropout are reviewed in (Hespanha, Naghshtabrizi and Xu, 2007). Different elements of NCS like sensors, actuators, and controllers can communicate through a shared band-limited digital communication network. Most of NCS studies have been conducted to improve performance of the controller by eliminating effects of these issues in presence of a given shared lossy wireless network. However, the network design based on control requirements results in a high-performance controller. The different classes of applications require improvement in some of communication challenges, such as delay, fading, interference and etc. In all networked control systems, a major challenge is network delay, which may degrade the overall system performance, but this is more significant in wireless communications (Santos and Block, 2012).

In NCS designs for the automotive applications, configuring a synchronous time-triggered scheduling network plays an important role in delay reduction and signal-interfering avoidance. A proper configuration requires a proper communication scheduling for ECUs and communication framework. In such systems, scheduling configuration should consider constraints of all communication networks and system dynamics to properly introduce commence time for each action and message assignment to slots. A desirable scheduling framework utilizes combinations of computational solvers to reach an efficient and modular configuration for the entire system (Goswami et al., 2012).

6.2 Design Criteria

6.2.1 Relative Sensor Importance

The benefits of embedding multiple sensors for redundant monitoring of a phenomina have been presented many times with examples for tractor truck operation. In these examples, there are essential sensors that provide critical primary information (feedback) needed to successfully manage system operation, and there are or may be secondary or optional sensors that are used to monitor either secondary parameters or to enhance the reliability (e.g. fault tolerance) of primary sensor systems.

An example case involving these two classes to sensor importance is where the sensor(s) indicating critical parameters may be too fragile and prone to frequent failure or degradation (ex. nonlinear temperature effects). Any vital sensor being significantly degraded or losing output (data) may cause catastrophic system failure. In such situations, if the sensors are too expensive to replace or are located in an inaccessible location within the system and it is not possible to replace or repair them when the system is in operation without other consequences (altering the system, downtime costs incurred as a result of shutting down the system for repair, etc.), it is desirable to provide some failsafe provision for obtaining these critical measurands, in case of a loss of information from their corresponding sensors.

With the use of a Bayesian network to provide functional redundancy, data from one or more of the other operational sensors can be used to send evidence to the network, and the value of the node corresponding to the sensor of interest. Condition based maintenance can be aided from this approach by defining high consumable and high priority sensors. This analysis would shape the basis for a commercial maintenance program.

6.2.2 Causality

Bayesian networks are highly influenced by node ordering (Nadkarni and Shenoy, 2004). Bayesian network links only represent conditional independencies and not necessarily represent causal relationships among those nodes. Using causal relations to represent the Bayesian links between the nodes can help attribute physical meaning – essential for engineering design – to the values that are obtained using the network, resulting in a more intuitive setup for users to comprehend those values for a better decision-making process.

For instance, consider a network with two nodes, current and torque, representing a motor. Assume that comprehensive experimental data regarding both the variables is available over the entire operating range in an application where the motor is used and can be used to create the required Conditional Probability Tables

(CPTs). The relation between them can be represented as two possible network structures as shown in Figures 6.1(a) and (b). From a mathematical perspective, both of the above networks are equally valid since both forward and inverse probabilistic reasoning based on available information, that is, *P(Torque|Current)* or *P(Current|Torque)*, are possible by simply using the CPT or Bayes' theorem, as the case may be. But for both experts (who are involved in designing the system and its Bayesian network representation) and nonexperts (who may be the end users making the final decisions for operating the system), the structure shown in Figure 6.1(a) will provide a greater intuition in decision-making since it represents what actually happens in a motor, that is, the current applied across the motor windings results in torque generated by the motor (due to the air-gap magnetic field) and not the other way around, with the torque generated being directly proportional to the magnitude of the supplied current.

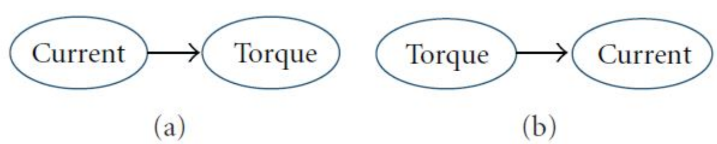

Figure 6.1: Causality can be a powerful tool for system configuration and must be considered when designing the information flow network.

6.2.3 Sensor Reliability

Sensors are affected by numerous factors in their operational environment and from their demands (that change over time in most production systems). Factors like duty cycle, heat/temperature, mechanical shock/vibrations, humidity, power-on/power-off cycling, and so forth, can detrimentally affect sensor components, especially electronic ones (Denton, 2010). In most setups, sensor data is acquired by a Data Acquisition Device (DAQ) computer system and processed into useful information (performance maps) that may be used for decision-making. In this process, data from sensors may become unavailable due to a sensor fault (such as a sensor contact wear or degrading communication capability) output signal to the processor. These factors or possible scenarios must be considered in evaluating how reliable a sensor is.

Reliability is often expressed as the probability that the sensor will function without significant failure over a certain time or a specified number of cycles of use (similar to material strength methods). A common metric for specifying reliability indirectly is in terms of Mean Time Between Failure (MTBF), which is the average expected time between failures of like units under like conditions. It is typically calculated based on installed equipment (MTBF = total time exposure for all installed units/number of failures). Such information is rarely provided in the sensor specifications from manufacturers due to factors like the lack of a standard measure for reliability, the need for accelerated life testing under extreme environmental conditions, and so forth. This information is generally expensive and is difficult to collect and expedite.

However, if such data is available for any system, based on the system operational history and the various sensors integrated into it, the knowledge may be used to refine the structure of the Bayesian network for future versions of the system. The nodes corresponding to sensors traditionally found to be highly significantly reliable should be connected to as many other nodes as possible to distribute high quality information flow throughout the network.

6.2.4 Computational Complexity

With the development of a variety of inferencing algorithms and advances in computational power, the use of Bayesian networks as a tool for both modeling and decision-making has been increasing in many domains for objectives like diagnosis, fault detection, classification, and so forth. The extent a system is accurately represented by the model and the quality of results obtained using the model are direct functions of the network structure. (Nadkarni and Shenoy, 2004) demonstrated that inferencing algorithms are as sensitive to the network structure as the probability values encoded in the different node CPTs. From the demonstration, the most effective net-

works seem to be those that combine sound expert knowledge to define the network structure (qualitative) and use extensive data to identify/refine the probability values of the variables represented by the nodes in the network (quantitative). However, despite the value of such a knowledge-based approach (Nadkarni and Shenoy, 2004), there is no prescribed method to construct the network structure when done by domain experts.

The process of creating the network structure based on expert opinion is iterative. A basic structure is first created and then refined based on feedback from other experts (often the direction of links that result from this process imply causality). Then, using the preliminary structure, the network may be implemented under real-world conditions (with components like a graphical user interface, visualization tools, etc., added) to carry out a particular task. This is done to verify its ease of use and intuitiveness in conveying the system characteristics to the end user. Based on user feedback, the network may once again be modified, if necessary, for better usability. If it is found that the results obtained using the network are not satisfactory (or worse, contradictory to those expected based on expert opinion or user experience), its structure may need further refinement. At each iteration, links or nodes may be added to the network or they may be pruned, the direction of some links may be reversed, and so forth. These small changes may or may

not always be beneficial. In some cases, they may possibly diminish the efficacy of the network in achieving its intended purpose (since each change may affect factors like the size of node CPTs, type of data/experimentation needed to estimate the CPT parameters, etc.).

Consider a case where a domain expert creates a network for a system with a set $\boldsymbol{X}$ of critical variables and a set $\boldsymbol{Y}$ of variables of secondary importance. In such a case, it would be imperative to represent all the variables in $\boldsymbol{X}$ as nodes in the network, but the expert has to make subjective choices regarding how many/which specific variables from $\boldsymbol{Y}$ also need to be included in the network, if these variables are measurable, their relevance to the variables in $\boldsymbol{X}$ as well as to the goals of creating the network, and so forth. If such a network is intended to be used for real-time operation, then the insertion of numerous additional nodes into the network or a high degree of interlinking between the nodes in $\boldsymbol{X}$ and $\boldsymbol{Y}$ may render it too intractable to satisfy the real-time operation criterion (large CPTs can prove to be a computational hindrance in such cases due to the longer times needed to parse and extract values from the CPTs in inferencing algorithms, especially if the CPT is sparsely populated, or individual state probabilities are low and widely spread, etc.).

Designers should note that while more nodes in a network can result in a greater confidence in the sensors and the system, they

come with a computational overload. The network structure has to be matched to the computation power available.

6.2.5 Redundant Sensors

In general, adding nodes to a network increases effectiveness in achieving the application objectives in regards to proper fault identification, (Subrahmanya, Shin and Meckl, 2010). Consider the network in Figure 6.2(a) designed for decision making in a condition monitoring application. Assume each network node represents a sensor corresponding to a domain variable of interest and each link represents a physical process that transforms the variable represented by the parent node to the one represented by the child node. With any unexpected deviations in sensor readings, the challenge facing the decision maker who operates the system is to decide if the variations indicate a potential fault in one or more sensors or whether they are indicative of a fault in the monitored system. If the variations are inadvertently attributed to faulty sensors when in reality, they may be the result of degradation in one of the system's subcomponents, it can result in a *false alarm* from the condition-monitoring algorithm that utilizes this network.

(Krishnamoorthy, 2010) presents a novel Bayesian network-based algorithm to detect and isolate the cause of such deviations. The developed algorithm required additional nodes (sensor redun-

dancy) to distinguish between sensor and system (component) faults. Redundancy increases network size, increasing computation resources and complication, however, the redundant nodes enable superior fault detection. The intended network use must always be taken into consideration while designing and before finalizing network structure.

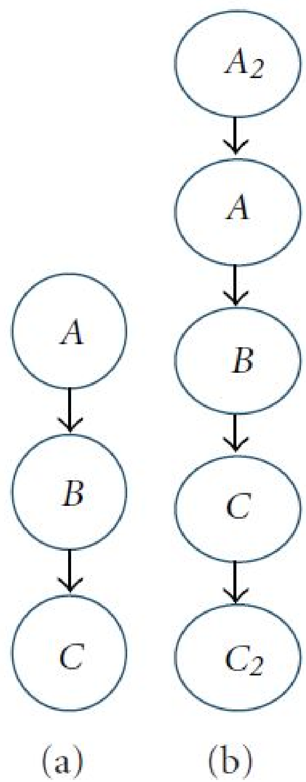

Figure 6.2: Use of redundant nodes.

Chapter 7

Data Flow for Complex Real-Time Decision Making

Nearly all productive (real) mechanical systems are inherently nonlinear. This nonlinearity enables their wide flexibility in task performance in the form of their multiple distinct output functions but also creates modeling and control challenges. Traditional methods for controlling mechanical systems involve developing a theoretical mathematic system model where the system behavior response is characterized by a set of differential or partial differential equations. Such an approach is successful for simple systems but rapidly unravels for inherently nonlinear, more complex, multi-input multi-output systems. Complexity in this sense means a complicated system that varies with time, such as wear and environment variation in mechanical systems.

Direct analytical relationships between the environment parameters and the system output are difficult to realize and the unmodeled effects will ultimately dominate the quality of the system's performance or control. Even when the analytical relationship ex-

ists, their inclusion in the mathematical model results in a highly complex coupled formulation unsolvable by continuum mathematics.

For example, a tractor truck can be sufficiently modeled with dozens of parameters to provide a highly nonlinear description of the actual physical response of the vehicle to a wide variety of expected conditions (Kim et al., 2016). However, this nonlinearity means there is no general solution using classical control methods and useful approximations will be difficult to produce in near real-time. Classical controllers tend to neglect these important nonlinear parameters in favor of simpler linearized formulations (Tesar, 2011).

Optimal, multi-variable, or multi-input multi-output control methods in addition to adaptive and nonlinear approaches always tend to establish working models of the system that impose conservative (sometimes very conservative, typically due to system stability concerns induced by the control method) ranges on the operational domain limiting performance capability of the system. For example an electro-mechanical actuator (EMA) in practice operates under the manufacturer's rated specifications. These specifications are conservatively estimated as there is little working knowledge about the actual operating condition (temperature, magnetic field saturation etc.). Lack of this needed awareness is because none or minimal sensors are or have been used to assess performance information about the machine under expected demand. An intelligent

actuator embedded with sensors can push the conservative performance limits during short periods of demand and thus be able to respond to a wider range of operating conditions and duty cycles as well as document performance to establish empirical relationships to characterize the machine for future optimization.

A more direct approach and awareness about the system is needed from that available from mere analytical methods. Numerous sensors are needed to obtain in real-time the physical operating conditions, to monitor actual parameters and develop a more complete view in real-time. In the past, the ability of the system to respond intelligently to unstructured environments was restricted by its capability to accurately sense and interpret the operating condition (Stieber, Petriu and Vukovih, 2006). The sensing technology either did not exist, was immature, or was not available in a small physical volume feasible to integrate into the system. Custom sensors were developed catering only to a particular system but these were expensive and did not allow use in multiple systems. Multi-sensor systems also add complexity to the system which requires data management and selection of the best possible options in real-time. Computational capabilities to deal with multi-sensor data were not sufficient or were not available at low cost (Khaleghi et al., 2013).

But in the last decade, sensor technology has increased re-

markably such that sensors are available with embedded computational capabilities in low cost and small size (Khaleghi et al., 2013). This surge in technology and manufacturing has made cost effective sensing and processing a wide range of phenomenon possible in real-time. Hence a new approach to intelligent control is needed where the use of actual data from the deployed sensors in real-time is properly used and caters to the performance requirement of the user. The roots of this criteria type and sensor based control approach can be found in the research of redundant robot manipulators where kinematic redundancy (extra resources) is exploited to achieve tasks like obstacle avoidance, increased dexterity, etc. Criteria can also be used to measure system performance.

A sensor model based on real-time data is essential in the criteria based control of an intelligent system as it accounts for unmodeled effects and drift in the parametric model of the tractor truck system. This system model is currently obtained through kinematic formulation with nonlinear aspects, such as tires and suspension, being modeled through metrology and emperical data. Merging the sensor model and the literature models can result in greater performance with understanding of how to further increase performance.

One of the arguments against using multiple sensors is that the addition of each sensor is a possible single point failure. But single point failures are avoided with the use of redundant sensors. The extra sensors either directly measure the same physical phenomenon or measure a different phenomenon having an established relationship with the desired phenomenon. These information networks, like a Bayesian Network, can be used to infer lost data, resulting in fault tolerance, detection and management by intelligent decision making.

7.1 Computational Intelligence

Computational intelligence is a generalization of machine system intelligence to enable decision making and conflict resolution for all complex systems under human command. Physics based systems are generally described by continuum mathematics, typically in the form of differential equations. This process of developing differential equation based models and solving them requires the specification of an initial and final condition, which is generally not known or is continuously modified by human intervention via operator commands.

Further, today's systems are constantly becoming more complex with concern for partial or complete failures making the use of sensor-based data acquisition necessary in real time (m-sec. or less). As mentioned before, true complexities of value refers to systems varying with time meaning a real-time control system has to constantly resolve the differential equation base model or, even worse, re-derive the entire system model as a critical relationship has been significantly changed over time, as is the case with mechanical deformations or wear in serial robot arms or vehicle tire-ground interface and with electrical chip burn-in where resistance levels change in an integrated environment.

The primary focus in developing intelligence in a machine is real-time decision making under human command/oversight of ever-more complex systems. This problem is compounded further with the allotted decision making time frame becoming smaller to increase performance. A framework is needed to provide an intelligent system designer the means to interpret and set system operational criteria, rank them, obtain detailed subsystem parametric descriptions via a metrology-type method, organize and interpret the system architecture, set up a task planner, create a configuration manager, and structure and evolve a domain-specific operational software. All of this has been fulfilled for computers. This work should encourage the use of intelligence in machines to a large scale.

Unfortunately, as presented before, this vast amount of operational choices and system operational criteria must be resolved in 10 to 100 m-sec. Performance maps must be combined into performance envelopes (for torque, efficiency, responsiveness, durability, etc.) which, then, become decision surfaces to drastically reduce

“guess work” or time-consuming hunting for a best-choice in performance. This is called structuring the decision process. Lessons learned can also create decision surfaces for a range of vehicle operational criteria. Choices on brake/throttle levels, actuator output levels, steering angle, and suspension or tire /wheel design can all be prioritized relative to some operating regimes proven under extensive testing.

What is clear is that a huge number of resources and criteria are now available to maximize vehicle performance relative to operator commands. These subsystems are primarily parallel, which permits subsystem optimum performance choices, which then can algebraically be summed to best meet system-level performance objectives. These objectives must be set by the vehicle operator by means of visual performance maps in real time. The operator also represents a distinct set of performance maps (obtained by direct measurement) which should be in balance with the vehicle’s performance maps. This is the opposite of autonomy where all decisions are made by computers with preset criteria and operational margins. The full benefit of this power utilization complexity as described here will not permit a simple open-loop set of autonomous decisions without continuous human oversight and corrective command decisions.

7.2 Operational Criteria

Once the intelligent system design is completed and a representative Bayesian network has been designed for it (see Chapter 5), suitable criteria must be determined for managing information from all sensors during system operation. This process ensures the best use of the data from the finite set of sensors and the network in conjunction with the available computational resources at any given time. These operational criteria may be used to make decisions regarding how the available sensors may be prioritized to adapt to varying task demands, determine the best options for sensors that may serve as alternatives used to infer the correct value of failed or degraded sensors, determine what sort of information can be gleaned from the sensor network, account for constraints that may arise during operation like reduced bandwidth/power, decide on algorithms that are best suited to meet the on-demand application constraints such as maximum performance verses economic operation.

7.2.1 Bayesian Nodes

Relating all the target system variables using a Bayesian network allows the use of any variable to infer the value of any other variable in the network (by setting the former as evidence and using probabilistic propagation to infer the desired value). However, the inferred value (and the uncertainty in it) can be heavily influenced by the number of intermediate links between the evidence node and the query node.

As an operational criterion, node distance may be used to determine the sensor that is most likely to give a best estimate of another measurand. The smaller the node distance, the better the estimate (mechanical stiffness and numerical accuracy in computation may be a suitable analogies).

7.2.2 Sensor Health Status

The primary goal of integrating sensors into any system is to provide real-time feedback on the measurands of interest for control purposes and enable the system to successfully accomplish its task. An equally important task for both the essential and secondary or optional sensors in intelligent systems is to enable correct monitoring of parameter variations by providing reliable and accurate data, eventually leading to updated relevant performance maps over time. The goal for this topic is to track the overall health of the system using condition-based maintenance algorithms to ensure a continued availability of the system as well as to assist the human decision maker in determining the ability of the system to accomplish the required tasks.

A sensor can be considered "healthy" if it produces an output signal proportionally and correctly to the input stimulus. Correctly

means within an acceptable amount of deviation as dictated by the sensor physics, resolution, accuracy, application requirements, and so forth (see Chapter 4 & 5). However, as mentioned earlier, the output from the sensors can be affected during regular operation by a number of factors that can be considered as faults in a sensor that occur intermittently or they may occur consistently over an extended period indicating the development of gradual sensor faults. In the extreme case, there may be a complete loss of information from a sensor due to an abrupt failure of the sensing element or its peripherals like power/signal transmission lines, connectors, faults in the onboard signal processing circuits, and so forth. When the required sensor readings become unavailable or when erroneous sensor readings are used for control purposes, it may lead to undesirable system behavior.

Furthermore, using data from faulty sensors to update performance maps, without checking for their validity will result in corruption of the stored maps. This, in turn, may lead to false alarms and missed detection of system faults from the system-level CBM algorithms. In each situation, the health of all the sensors must therefore be taken into account by the system operator in deciding whether or not to utilize the data from a particular sensor. To this end, (Krishnamoorthy, Ashok and Tesar, 2015) presents the development of a novel Sensor and Process Fault (SPF) detection

and isolation algorithm that can help quantify the trustworthiness of the information from a sensor. Belief values are assigned to the various sensors and processes in the system which is represented using a Bayesian network. Analytical estimates for the various physical quantities represented by the nodes in the network are calculated using standard Bayesian network inferencing algorithms. By comparing these values against the actual values indicated by the sensors corresponding to those quantities and modifying the belief values based on the results of the comparison, the algorithm provides an indication of the potential source of the fault (i.e., a specific sensor or a group of sensors or a specific process). These belief values provide an intuitive metric representing the health of each sensor that the decision makers can then use in their assessment.

Sensor health status is an important criterion that the Human Decision Maker (HDM) could use to disable a failed sensor, so decisions and control are not based on faulty sensor readings. It is very important that sensor failure is distinguished from process degradation and this is enabled by the algorithm presented in (Krishnamoorthy, Ashok and Tesar, 2015). Additional background and more detailed application can be found (Denton, 2010) and (Jo et al., 2017), receptively.

7.2.3 Resource Availability

In most applications, following some preliminary processing at the sensor-level, the signals from all the sensors monitoring the system are sent to a central location for further processing or for use in deriving higher level information. This configuration is commonly observed in PC-based data acquisition and control of systems like Electromechanical Actuators (EMAs), mobile robots, and so forth (Krishnamoorthy, Ashok and Tesar, 2015). With a limited number of sensors, a point-to- point connection technique is sufficient to connect the sensors directly to the PC without significant design or hardware overhead. However, such an arrangement requires complex cabling arrangements. Hence a bus topology is often utilized wherein all the sensors use a common set of resources for data transmission. In a digital field bus system, multiple sensors are connected via shared digital communication lines (reducing the number of cables) to transmit/receive data more efficiently on an as needed basis. When such an arrangement is utilized, the cumulative data bandwidth and latency required for all the sensors being considered play a significant role in the selection of the appropriate bus. The bus design is a function of sensor output type, quantity of output data generated in a specific time period, sampling rate for different sensors, mode of acquisition from multiple sensors (simultaneous/multiplexed), and so forth.

With fewer sensors, the total bandwidth requirements are moderate, and it may be possible to sample all the sensors simultaneously with the available data bus and acquisition hardware resources. However, if the system has a large number of sensors which also need to be sampled at high rates, the number of high-speed data acquisition channels required increases (to accommodate the increased bandwidth/sampling requirements) which typically leads to higher overall costs. Often, as a compromise between cost and performance requirements, a limited number of data acquisition channels are used (capable of handling large amounts of data at high frequencies) and the available resources are distributed across all the sensor channels, by using a lower sampling rate, polling the sensors periodically instead of continuous acquisition, and so forth.

The use of a Bayesian network to model the system allows the flexibility of inferring the value of any node/ variable in the network (query) using the value of any other node/variable (evidence) in an inferencing process. This capability can be exploited for managing the available resources (bandwidth/sampling rate capability) in certain operating regimes of the system, where it may not be possible to accurately acquire data from sensors with demanding requirements (i.e., those that require a high bandwidth/ sampling rate). For instance, in the actuator example cited earlier, if the motor rotates at 6000 rpm, the output frequency from the encoder rises to

1MHz. If the associated data bus and acquisition hardware are capable of accommodating only 0.5MHz, it might be more prudent to allocate the available resources to sensors with modest resource requirements the voltage sensors which need to be sampled at only 1 kHz to acquire their output data with the best possible resolution/sampling rates. This data may then be used to infer the values of other variables that have higher bandwidth/sampling rate needs such as motor speed (within reasonable accuracy) using a Bayesian network that includes the motor voltage and speed as nodes.

Different operational regimes utilize different hardware resources. Resource availability is a criterion that can be used in real-time to determine the set of sensors that can be enabled or disabled in real-time as the situation demands.

7.3 Asynchronous Data Flow

A significant practical problem in collecting sensor data in a multi-sensor system is that the target data reported by the sensors are usually not time-coincident or synchronous due to the different data rates and deriving a common reference time for bias estimation is often difficult. Most literature solely focuses on synchronous systems where there is no need to develop common reference timing to implement a controller. Essentially this requires time-varying (as opposed to invarying) measurement models.

A hierarchical programming language for modal multi-rate real-time stream processing applications (such as our smart truck case) was developed in (Geuns, Hausmans and Bekooij, 2014) to address the concerns in sequential programming languages of handling multi-rate behavior or asynchronous dependence and with parallel programming languages where deadlock-freedom and sufficient throughput cannot be guaranteed. The crucial aspect of this approach is the ability to sequentially specify application behavior in a manner that can be nested in a concurrent specification. Multi-rate behavior can be conveniently expressed using concurrent modules which have well-defined, but restricted interfaces.

In this approach, a system monitoring or control program contains multi-rate behavior if the sample rate of data is changed. The task graph in Figure 7.1 shows an example, from (Geuns, Hausmans and Bekooij, 2014), of such multi-rate behavior where task t_f first reads three values and T time later writes three values and task t_g reads only two values and writes two values T time later. Both tasks execute data-driven, meaning they execute when sufficient data is available at their inputs. Because both tasks read a different number of values, task t_g must execute $3/2$ as often as task t_f . The dot labeled 4 indicates that four initial values are available for task t_f to read.

Writing such a cyclic application as a sequential program can

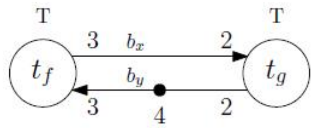

Figure 7.1: Task graph for multi-rate behavior (Geuns, Hausmans and Bekooij, 2014).

be difficult as often the only option is to specify the complete schedule until the initial state is reached again. This is illustrated by the sequential program in the Figure 7.2 below where a schedule is shown for the task graph in Figure 7.1.

```
int x[6], y[6];

init(out y[0:3]);
loop{
  f(out x[0:2], y[0:2]);
  g(out y[4:5], x[0:1]);
  f(out x[3:5], y[3:5]);
  g(out y[0:1], x[2:3]);
  g(out y[2:3], x[4:5]);
} while(1);
```

Figure 7.2: Sequential program for multi-rate behavior (Geuns, Hausmans and Bekooij, 2014).

A Compositional Temporal Analysis (CTA) model, from (Geuns, Hausmans and Bekooij, 2014),is used for verifying if the real-time constraints of a program are met and to determine sufficient buffer capacities (for significant rate differences). The CTA model consists of components, depicted as rectangles on the right in Figure 7.3 and connections, depicted as arrows. Data is transferred periodically between components over connections at a given rate. A

connection can delay a transfer by a pre-defined amount of time.

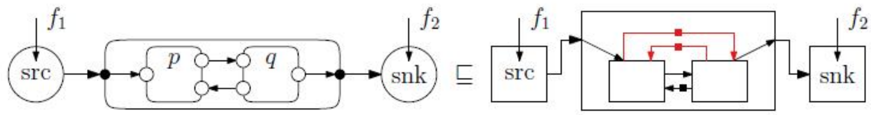

Figure 7.3: Refinement of temporal analysis (Geuns, Hausmans and Bekooij, 2014).

In Figure 7.3, data is produced by a source *src* at a rate f_1, is processed by a module, depicted by the outer rectangle, and transferred to a sink *snk*, which consumes data at a rate f_1. Processing is done in two while-loops, represented by the inner rectangles. The number of iterations of these loops is given by the parameters *p* and *q* respectively.

Figure 7.3 illustrates the corresponding CTA model, which is constructed from a program such that for every module and every while-loop a CTA component is extracted from modules nest CTA components corresponding to while-loops. Essentially, the topology of a CTA model is equivalent to a program. However, a CTA component is not parameterized and is always active at a given periodic rate. Therefore, while-loops cannot be directly modeled as CTA components.

(Geuns, Hausmans and Bekooij, 2014) present the intuition behind the abstraction made to model a while-loop as a CTA component. They show that the abstraction of a parameterized while-loop

to a CTA component with periodic rates is allowed, by guaranteeing that every (electrical) source and sink can execute strictly periodically. To ensure a bounded time between accesses to a source or sink, they must be accessed in every while-loop iteration. In the CTA model this implies that every component corresponding with a while-loop has an access to every source and sink. Thus on the right in the Figure 7.3, the two nested components access both *src* and *snk* as illustrated by the connections.

This work provides a logical construct to interconnect complex (complicated interactions that vary with time) systems in a manner that sufficiently handles asynchronous monitoring and control and also provides a graphical means to illustrate connections. The cited paper, (Geuns, Hausmans and Bekooij, 2014), should be reviewed for details on implementation.

A similar work was conducted in (Wyss et al., 2012) with a focus on aircraft control. The approach here is to avoid "overspecifying" a program by developing an extension of synchronous data flow languages where the designer can specify that he does not care whether some communication is immediate or delayed. It is then up to the compiler to choose where to introduce delays, in a way that breaks causality cycles and satisfies latency requirements imposed on the system.

In (Wyss et al., 2012), the authors consider a simplified mono-

periodic flight control system depicted in Figure 7.4. It consists of a set of avionics functions, which acquire information on the state of the aircraft and on the pilot orders, with the objective to control the position, speed and attitude of the vehicle with its control surfaces. The right part of the figure depicts the control of the ailerons while the left part depicts the control of the elevators. Each vertex depicts a function. Edges depict data-communications between functions and are of two different kinds. Plain arrows stand for immediate communications, which induce a precedence constraint from the producer to the consumer. Dashed arrows stand for less constrained communications that do not induce precedence constraints.

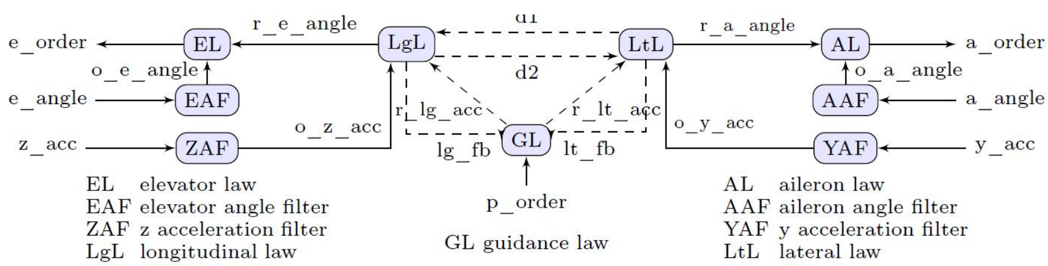

Figure 7.4: A simplified flight control system (Wyss et al., 2012).

7.3.1 Multiclock Train-Control Embedded Systems

There is also much to learn about asynchronous data flows from high speed integrated electronics for embedded real-time systems. Today's system-on-chip (SoC) and distributed systems are commonly equipped with multiple clocks where the key challenge in

design is that two situations have to be captured and evaluated in a single framework. The first is the heterogeneous control-oriented and data-oriented behaviors within one clock domain, and the second is the asynchronous communications between two (different) clock domains.

In (Jiang et al., 2015*a*,*b*), the authors use timed automata and synchronous dataflow to model the dynamic behaviors of the multiclock train-control system, and a multiprocessor architecture for the implementation from the model to a real system. Data-oriented behaviors are captured by synchronous dataflow, control-oriented behaviors are captured by timed automata, and asynchronous communications of the interclock domain can be modeled as an interface timed automaton or a synchronous dataflow module. The behaviors of synchronous dataflow are interpreted by some equivalent timed automata to maintain the semantic consistency of the mixed model. Then, various functional properties that are important to guarantee the correctness of the system can be simulated and verified within the framework.

Embedded systems are being widely used in all kinds of applications and are traditionally designed and optimized using a synchronous language with a single clock. Such an assumption of global synchronization greatly helps reduce the complexity of the design. Very often, an embedded system contains both data-oriented and

control-oriented parts. The control-oriented systems control large amounts of decision logic that has to quickly produce output in response to input events, while in data-dominated systems, intensive computations have to be performed on samples that usually arrive in regular intervals. For example, the cell phone contains not only the control-oriented network communication protocols running on the processor but also the data-dominated algorithms for dealing with the voice signal. Furthermore, embedded systems are increasingly adopting multiclock solutions due to the low-power requirement and the pervasive usage of IPs from different vendors. This is particularly true for the train-control system described in the standard international electrotechnical commission (IEC) 61 375. Hence, there has been a recent surge for methods to guarantee the functional and sequential correctness when designing multiclock train-control systems.

To model the multiclock train-control system with both data-oriented behaviors and control-oriented behaviors, a set of timed automata and synchronous dataflow modules are composed into a network over a set of clocks and actions with parallel composition operators. The data-oriented, control-oriented, and multiclock domain compositions make the proposed model closer to the real implementation. (Jiang et al., 2015*a*,*b*) demonstrate that in the design process, different design models derived from requirements with simulation and formal verification techniques, avoid potential errors that may lead to rework, and choose the best one. In the implementation process, (Jiang et al., 2015*a*,*b*) show that the model can be abstracted from the implemented system and be evaluated with simulation and formal verification techniques to validate whether the system meets the requirements or not. The overall framework is depicted in the Figure 7.5.

7.4 Potential Applications

7.4.1 Conditional Maintenance

Condition-Based Maintenance (CBM) is a supervisory control algorithm that is solely dedicated to monitoring machine systems or processes in order to detect and diagnose incipient faults at an early stage. By providing an early warning of potential failures, *preemptive maintenance* (fix before broken) may be carried out rather than reactive maintenance (Chow, 1997). The underlying principle upon which CBM operates is that machines provide advanced warning of failure through symptomatic performance degradation. By detecting and identifying these symptoms early in their onset, maintenance may be carried out before system safety and availability are compromised.

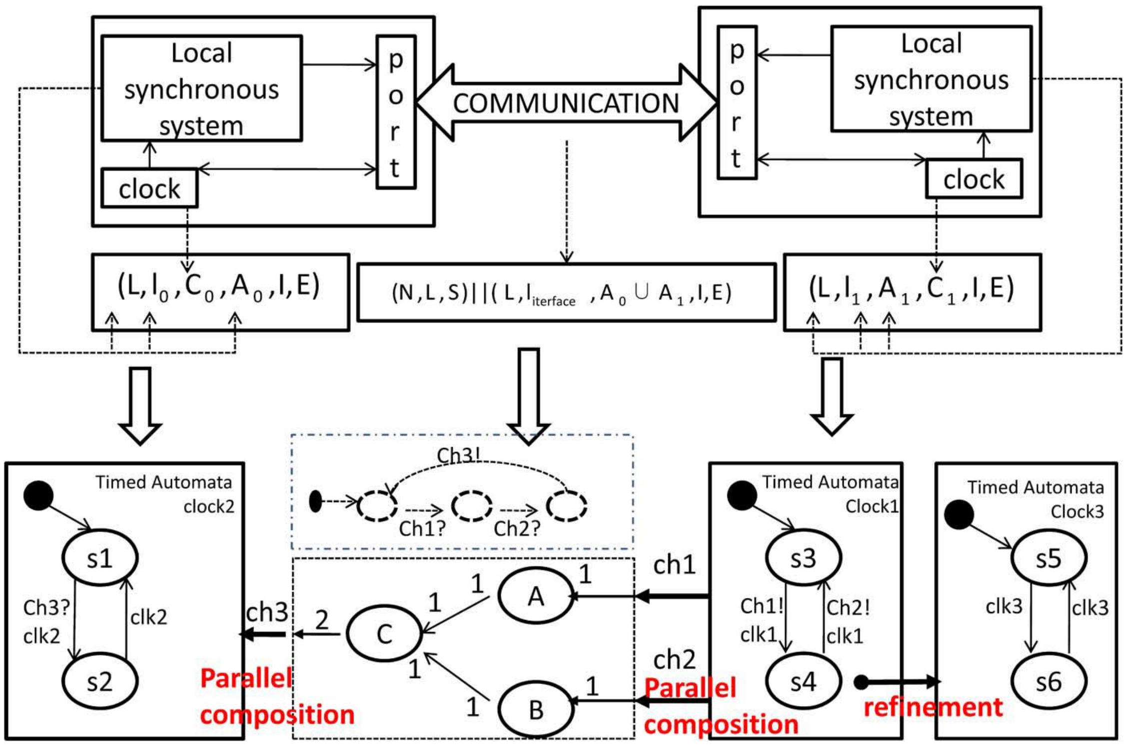

Figure 7.5: Modeling framework for multiclock embedded system with heterogeneous behaviors. Each local synchronous component is modeled as a timed automaton with clock remapping and refinement of states. Each data-oriented component is modeled as a synchronous dataflow module. The asynchronous communication is modeled as a synchronous dataflow module or a timed automaton with input/output channels (Jiang et al., 2015*a*,*b*).

7.4.2 Creating, Updating, & Enhancing Design Maps

All intelligent systems are inherently complex (many operational tasks and goals varying over time), and they are increasingly nonlinear and highly coupled with ever changing criteria for good operation. These criteria are best presented as parametrically based maps (efficiency, force level, temperature, noise, etc.)

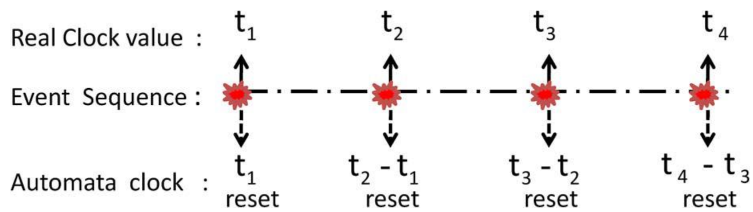

Figure 7.6: The real clock value is mapped to the local clock in timed automata to ensure synchronous reaction behaviors. The real clock is redefined as some intervals. Those intervals are defined on the basic clock of timed automata (Jiang et al., 2015*a*,*b*).

that can be presented visually to a human operator or to become a way to structure the decision process (moving towards envelopes with sweet spots or danger zones) for directed computational procedures to augment the operator's ability to make the best decision. Hence, maintenance (updating) of the maps keeps the decision process timely and relevant. This human supervised process is then what is really meant by system intelligence. Updating the maps accounts for changes in the system (wear, material changes, wiring resistance changes, etc.) This updating can also generate lessons learned for archiving and future system design development. None of these objectives could be achieved without a full sensor network generating real-time data to represent the system.

7.4.3 Driver Characterization

Characterizing an operator has many opportunities to improve overall efficiency and effectiveness. The ultimate technical

need is to develop a formal procedure to obtain basic (classical or fundamental) performance maps for representative classes of truck drivers. These maps, then, parametrically represent the real performance of the driver under a wide range of conditions so that they can be combined on demand into decision making envelopes to visually aid the driver to self-regulate his/her decision capacity and to transmit his actual performance to a connected oversight structure as part of an intelligent truck network.

The monitoring of real-time human performance can increasingly be considered based on data generated by a wide array of existing low cost body sensors (McFarland, 2011). Further, these body sensors enable this real time data to be analyzed (interpreted) by algorithms now being developed in the scientific community. For example, heart rate may be closely related to physical activity (or the lack of it). A sudden rise in body temperature may indicate a limiting illness. Simple eye activity sensor data may indicate lowered eye motion and a lack of attention or drowsiness. Perhaps, simple brain signal sensors (in a cap) could indicate lower or erratic brain activity. The following is a list of available sensors that could be used in a digital network to generate multiple assessments of a truck driver's performance level (McFarland, 2011):

temperature	**accelerometer**
skin moisture	**inertial sensors**
glucose level	**blood pressure**
eye activity	**heart rate**
breathing rate	**oximeter (blood oxygen)**
brain waves	**electrocardiograph (ECG)**
acoustic voice	**photoplethryomorgraph (PPG)**

Based on this collection of data, several performance measures such as: endurance, responsiveness, cognition, fatigue, stress level, etc., may be represented as 3-D maps describing performance over a wide range of the measured data (parameters). These maps enable excellent visual understanding of an individual's level of capability. Further, these maps are easily transmitted to other crew members or to a truck network manager. Hence, in-depth self-awareness of team effectiveness can be continually monitored and assessed by all decision makers in the network. All recorded operator performance maps would represent "sweet spots" for expected good performance and danger zones where performance may be below essential performance levels needed for good decision making. A finite number of maps would always be on display where the data would generate a performance indicator (a green dot) which shows where the operator is on their map so they can take corrective action if necessary (or guidance can come from the network or the driver's manager).

Of course, obtaining meaningful maps for truck operators, in general, and for a given operator is a significant but essential effort

to truly enhance the operator's performance and to identify when that performance begins to degrade. This degradation measure will be one of the most difficult to achieve since the maps must be numerically updated in real time. Once an updated map(s) exists, it can be differenced with the reference map(s) and the difference(s) would give the most accurate representation of the operator's overall capability. This is actually a core capability for the assessment of all electro-mechanical systems, as well.

Given updated maps for the operator and the system, these can be matched (melded together) to assess the capability of the human and machine combination. Doing so would accelerate the development of all systems under human command (shifting away from autonomy, which is frequently associated with robotics). This approach for the truck driver/tractor truck combination is described in more detail in section 8.3 – Human Interfacing.

Clearly, this performance map capability can be applied to the assessment of drivers in training and then to show the beginning driver how to improve their performance maps by visual representation of that improvement. Experienced drivers' maps could also be used to show the trainee where improvement would be desirable. Finally, self-awareness is the ultimate goal since much of his operation as a truck driver is an isolated activity. All of this dramatically reduces guesswork based on intuition in favor of numerical docu-

mentation, which gives all parties a reliable basis for improvement and oversight.

Chapter 8

Future Development

8.1 Sensor Development

In this document potential advantages of multi-sensor systems were presented with a focus on tractor truck vehicle systems. Articulated heavy vehicles (AHVs) are widely used cost-effective transport vehicles for goods, however, AHVs exhibit low lateral stability in terms of unstable motion modes, including trailer swaying, jack-knifing, and roll-over, which frequently causes fatal accidents on highways. A framework for developing a multi-sensor architecture for articulated trucks was established throughout this document as well as methods and references for realistic implementation of such a system.

An overview of relevant sensor and associated technologies was detailed, however, as a network of body sensors to monitor the physical condition of a driver in real-time was indicated to be valuable. A wide variety of biofeedback sensors is available commercially that can give information about physiological conditions such as heart rate, skin temperature, perspiration, muscle tone, eye pupil movement, brainwave signals, respiration, etc. More survey work needs to be conducted along this aspect.

It may be infeasible to include all the sensors at once for actual system development and implementation. Selecting a small set of technologically mature, high priority sensors, integrating them in a network and acquiring real-time data from these sensors for a selected set of operations should occur first. The crucial step would then be to analyze and interpret sensor data, show relationships among data from different sensors, establish statistical correlation, infer the same information from different sensors, and use the sensor information for intelligent control. This initial effort should focus on demonstrating the feasibility of a multi-sensor intelligent system and should clearly illustrate its advantages to justify further development. This kind of demonstration can take advantage of structured decision making theory (Ashok and Tesar, 2008) and Bayesian network based sensor and process fault management techniques (Ashok, Krishnamoorthy and Tesar, 2011) to prove enhanced performance of complex systems in a multi-sensor environment.

8.2 Sensor Integration

This document introduced and detailed the importance of data redundancy, which is extended to sensor redundancy. Single point failure modes already exist in the tractor truck system and the proposed system intelligence scheme will aid in adding greater control to dealing with these failures. Adding single point failures to the vehicle system by incorporating sensors is completely unacceptable. In fact, fault tolerance and condition based maintainance (CBM) are the result of system intelligence, ultimately leading to more productive and safer truck systems that have increased maintainability and reconfigurablity for pivoting to new demands.

The primary technology behind system intelligence that these benefits result from is sensor data management with Bayesian networks or Kalman filtering that can infer lost or poor sensor data. Related technology on developing reliable data/network structures that can be reconfigurable on demand were also detailed. Sensor physical durability and ruggedness was an important topic beyond the scope of this document but that should be considered.

8.3 Human Interfacing

Autonomy is being considered for cross-country truck operation to reduce the operation cost (less dependence on on-board drivers), improved safety (more rapid and accurate response to unsafe conditions) and improved fuel efficiency (better balanced wheel traction control). Present truck tractors require 100% of the truck driver's attention for their on-road operation. This is an expense that has been a high burden for truck transport. Further, railroad freight trains will also go through a revolution for cost effectiveness, timely delivery, and safety. To remain competitive, the truck industry must not only reduce expenses, it must also improve its level of safety to maintain the public's acceptance of its use of the national highways. Autonomy is not going to be a simplistic superposition of sensor-based decision making to replace human operator decisions. It will obtain its real goals if the truck tractor (and also the trailer) is made responsive to much higher levels of command in real-time (10 m-sec.). Doing so will create a balanced technology (decision making, sensors for real time operational data, tuned diesels for maximum efficiency, distributed choices throughout the driveline, and no single point failures), all combined for a revolution in truck tractors and vehicles, in general.

Both the human operator and the system must have an "intelligent" relationship to best improve human–machine interface. This document detailed that representing both the human and truck (machine) system with performance maps created from sufficient sensor data is an effective method for developing intelligent systems. These maps can be related and combined to discover potential performance envelopes to be improved, creating the basis for newer intelligent system design.

For the truck driver, real-time data on the vehicle can be used to enhance reaction time and options, efficiency, and reduce

driver fatigue. Additionally, the truck network supervisor, who is off-board, can now more effectively assist, govern, or even operate a network of trucks, reacting to potential human or system failures. Measures for cost effectiveness, safety, efficiency, etc. all demand intelligence in decision making. This begins with accurate operational data for self-awareness and self-regulation, which requires a robust distributed network of embedded sensors – the principal focus of this document.

8.4 Sensors & Actuator Intelligence

Given independent torque control (including braking) of each truck tractor wheel, it becomes possible to manage torque commands to each wheel (in m-sec.) to enhance traction efficiency, improve safety in rapid maneuvers, reduce tire wear, improve overall efficiency, and respond to overlaid autonomy guidance. This torque control involves look-up performance maps for tire traction under various surface conditions (asphalt, concrete, rain, cold, snow, ice, etc.), the need for criteria-based control of the tractor in less than 10 m-sec.to respond to driver commands (cold, raining, complex traffic, windy, etc.) and the ability to avoid single points of failure by rebalancing wheel torques, should one wheel degrade or fail.

8.4.1 Highway Grade/Traffic Data To Increase Vehicle Fuel Efficiency

Increasing vehicle intelligence (active traction control, hybrid energy management, condition-based maintenance, real-time driver assistance, etc.) now enables a real-time response to data for traffic conditions, grade levels, weather conditions, interruptions, etc. to maximize fuel efficiency of all surface vehicles (cars, trucks, freight trains, etc.). This data will be available through GPS, through mile marker registered grade levels, through broadcast weather conditions, on-board sensors for influence of traffic, wind, temperature, rain, etc.

The U.S. federal government has set very high fuel efficiency goals for all road vehicles (including tractor trucks). This is not simply a sensor data/decision making problem. It requires the full integration of all technologies (sensors, embedded component and system performance data, responsive multi-configuration drivelines, intelligent command/response actuators, real-time decision making software for each vehicle class, etc.). Hence, all technologies (electrical, mechanical, computational, etc.) must be brought together in balance and not treated as separate (or dominant) contributors to the solution (Tesar, 2016*c*).

Further, each class of system will have to enhance the performance levels of all component technologies. Hybrid vehicles will require increasingly efficient engines tuned to their sweet spot (torque, RPM, fuel/oxygen levels, etc.), efficient energy transfers to and from batteries, distributed transmissions with in-wheel drives, etc. For cars, this means a concentration on fuel efficiency and safety (and less on drivability), moving towards more "electric" systems. This certainly applies in the urban environment including fleet vehicles. For cross-country trucks, the tuned diesel engine must increase its efficiency by 25%, the drive line must be almost perfectly efficient, and traction control at each wheel must be used to further reduce losses and maintain performance levels. Diesel engines on tractor trucks represent an early version of an efficient power source. Tractor trucks could be improved further if the drivetrain was made more active with power distributed to active wheel drives on all trailers and in the truck. In laymen terms, improving actuator response in a system increases the value of sensing.

To get significant (2x initial estimate) efficiency improvement for road vehicles will require all technology domains to work together in balance. For example, clearly real-time traffic data impacts each vehicle's response commands. Wind impacts a truck's power demands. Intelligent in-wheel drives can monitor each wheel's traction to balance/minimize wheel slippage. Embedded efficiency performance maps for all active components can be used to stay in that component's sweet spot (engine, generators, motor drives, multi-speed drive wheels, battery energy reserves, etc.).

At the system level, data must be available to fully document (electronically define) all road conditions. This includes GPS/mile marker referenced road geometry (local speed limits, grade levels, curves, surface conditions, etc., if at all possible, at 1 ft. increments (note, that at 70 mph, 1 ft. represents a 10 m-sec. decision time span). In real-time on-board sensors must access all nearby traffic, provide performance levels for all on-board components and the system's integrated response capability, etc. This 1 m-sec. data must, then, respond to criteria continuously prioritized to maximize safety but also meet timelines and desired efficiency levels. Here, real-time operational decision making software with human-set priorities becomes dominant.

Artificial intelligence algorithms (predictive analytics) continuously assess this performance to refine performance maps, command/response capability, refinement of performance criteria, etc. All of this reflects the concentrated operational technology base already integrated in military fighter aircraft (Tesar, 2016*c*). Similar systems should be developed for commercial surface vehicles with a primary emphasis on safety (enhanced control/capability) and fuel efficiency.

8.4.2 Simulation with TruckSim

A future tool for developing multi-sensor decision making systems for tractor trucks could be using ***TruckSim*** along with ***Matlab-Simulink*** or ***LabVIEW***. Such a setup could implement a realistic vehicle and environmental models in ***TruckSim*** and implement emulated sensor data and control in ***Matlab-Simulink*** or ***LabVIEW*** (Sulaiman et al., 2012). This simulation environment provides a platform to develop decision making algorithms (test logic). Duplicating accident conditions in TruckSim would be a fundamental step before attempting to develop intelligence to avoid such conditions.

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Vita

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