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INTELLIGENCE-BASED SAFETY DECISION MODELS FOR TRAIN TRACTION CONTROL SYSTEMS

By

Kourosh Rafizadeh-Noori

Bachelor of Applied Science in Applied Mathematics in Computer

University of Kerman,

Kerman, Iran, 1994

A Thesis Presented to

Ryerson University

In partial fulfillment of the requirement for the degree of

Master of Applied Science

In the program of

Mechanical Engineering

Toronto, Ontario, Canada

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Intelligence-Based Safety Decision Models for Train Traction Control Systems

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Master of Applied Science, 2009

Mechanical Engineering

Ryerson University

ABSTRACT

In this thesis, two intelligence-based safety decision models for train traction control systems are proposed. These models are to prove the effectiveness of a modern method for speed sensor vehicles in a communication-based train control system (CBTC). Fuzzy theory and Bayesian decision theory have been modeled to learn and to classify the vehicle traction conditions using a pattern recognition concept. The proposed models are original and formulated for such integrated and complex systems like automatic train protection (ATP) and automatic train operation (ATO). In the intelligent format, the train traction's patterns are extracted and applied on speed sensors' input to classify the train traction. The error and risk of traction misclassification is also calculated to reduce the impact and exposure of safety and hazards. The proposed safety models are suitable for such a decision system due to processing the manageable number of state of natures (i.e., slip/spin, normal and slide), features (speed and acceleration) and having the prior knowledge of the vehicle's behavior which can be collected either from field tests or lab simulation. Both models involve a mathematical problem which can be solved in any programming language and to be used in the on-board or embedded computers. The conceptual models are applied to a hypothetical case study with promising results.

ACKNOWLEDGMENTS

It is my pleasure to acknowledge those who have encourages and supported me in many ways during my master research studies.

Firstly, I would like to thank my research supervisor Dr. Kouroush Jenab, for his outstanding supervision and guidance. His unconditional support, advice and constructive criticism throughout my research study have been invaluable.

I would like to thank Dr. Saeed Zolfaghari (Director of Industrial Engineering), Dr. Greg Kawall, (Director of Graduate Program) and Dr. Liping Fang (Chair of Department), all the faculty members, technical officers and administrative staff members for their kind support and cooperation all the time during my stay at Ryerson University.

I also record my special thanks to Mr. Woshiar Mavarani (Sr. Vehicle Engineer) for all his help and support along with proof reading of my thesis.

Finally, I should thank my family, especially my wife for her continued support, patience, love and many thanks to my parents for giving me a life opportunity and their unconditional support.

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NOMENCLATURE

θ_{wl}	Wheel diameter
υ_{pw}	Measured speed sensor's pulse width
κ_{pc}	Measured speed sensor's pulse count
ψ_{ppr}	Number of pulses per wheel rotation
D	Measured wheel distance
V	Measured wheel speed
$P(\omega_j \mid x)$	Posterior probability of *class* (ω_j) given the *feature* (x)
$p(x \mid \omega_j)$	Class conditional probability of *feature* (x) given the *class* (ω_j)
$P(\omega_j)$	Prior probability of *class* (ω_j)
$p(x)$	Probability density function of *feature* (x)
X	*d* components feature vector ($x_1, x_2, \ldots, x_d$)
μ	*d* components mean of feature vector ($x_1, x_2, \ldots, x_d$)
Σ	*d* by *d* covariance of feature matrix
$\lvert\Sigma\rvert$	Determinant of covariance of feature matrix
Σ^{-1}	Inverse of covariance of feature matrix
x_1	Delta speed feature

x_2	Train speed feature
ω_1	Spin/Slip state of nature
ω_2	Normal state of nature
ω_3	Slide state of nature
$P(\omega_1)$	Prior probability of slip
$P(\omega_2)$	Prior probability of normal
$P(\omega_3)$	Prior probability of slide
$\mu(\omega_1)$	Mean of slip
$\mu(\omega_2)$	Mean of normal
$\mu(\omega_3)$	Mean of slide
$v(\omega_1)$	Variance of slip
$v(\omega_2)$	Variance of normal
$v(\omega_3)$	Variance of slide
$p(X \mid \omega_1)$	Class conditional probability of feature vector (X) for given slip
$p(X \mid \omega_2)$	Class conditional probability of feature vector (X) for given normal
$p(X \mid \omega_3)$	Class conditional probability of feature vector (X) for given slide

$P(\omega_1 \mid X)$	Posterior probability of slip for given feature vector (X)
$P(\omega_2 \mid X)$	Posterior probability of normal for given feature vector (X)
$P(\omega_3 \mid X)$	Posterior probability of slide for given feature vector (X)
$\varphi(\alpha_i \mid \omega_j)$	Loss function of action (α_i) and state of nature (ω_j)
$R(\alpha_1 \mid X)$	Misclassification risk of action on slip condition
$R(\alpha_2 \mid X)$	Misclassification risk of action on normal condition
$R(\alpha_3 \mid X)$	Misclassification risk of action on slide condition
R	Real numbers
X	Universal Fuzzy set
$\widetilde{T}$	Traction Fuzzy sub-set
$\widetilde{N}$	Normal traction Fuzzy sub-set
$\widetilde{A}$	Abnormal traction Fuzzy sub-set
ρ	Received signal from speed sensor
ρ_0	Normal point signal from speed sensor
$\widetilde{\rho}$	Fuzzy number associate to received signal
$\mu_{\widetilde{T}}$	Fuzzy membership function for traction sub-set
$\mu_{\widetilde{N}}$	Fuzzy membership function for normal traction sub-set

$\mu_{\tilde{A}}$	Fuzzy membership function for abnormal traction sub-set
ω_1	Normal state of nature
ω_2	Abnormal state of nature
$P(\omega_1)$	Prior probability of normal
$P(\omega_2)$	Prior probability of abnormal
$\tilde{P}(x \mid \omega_j)$	Class conditional probability of *feature* (x) given the *class* (ω_j)
$\tilde{P}(a \mid \omega_1)$	Class conditional probability of acceleration (a) given normal traction
$\tilde{P}(a \mid \omega_2)$	Class conditional probability of acceleration (a) given abnormal traction
$\tilde{P}(\omega_j \mid x)$	Fuzzy posterior probability of *class* (ω_j) given the *feature* (x)
$\tilde{P}(\omega_1 \mid a)$	Fuzzy posterior probability of normal traction given acceleration (a)
$\tilde{P}(\omega_2 \mid a)$	Fuzzy posterior probability of abnormal traction given acceleration (a)
$\tilde{N}_\gamma$	$\gamma - level$ Normal traction Fuzzy sub-set
$\tilde{A}_\gamma$	$\gamma - level$ Abnormal traction Fuzzy sub-set
$\mu_{\tilde{N}_\gamma}$	$\gamma - level$ Fuzzy membership function for normal traction sub-set
$\mu_{\tilde{A}_\gamma}$	$\gamma - level$ Fuzzy membership function for abnormal traction sub-set
$F(a)$	Acceleration signal probabilistic distribution
λ	Exponential distribution time interval factor

O_i	Number of observation where i =1, 2, 3
ϕ_{Slip}	Number of slip observation in training set
ϕ_{Normal}	Number of normal observation in training set
ϕ_{Slide}	Number of slide observation in training set
ϕ_{Total}	Total number of observations in training set

ABBREVIATIONS

ABS	Anti Block System
ATC	Automatic Train Control
ATO	Automatic Train Operation
ATP	Automatic Train Protection
ATS	Automatic Train Supervision
CBTC	Communication-Based Train Control (Computer-based)
EMC	Electro Magnetic Compatibility
EMI	Electro Magnetic Interference
PPR	Pulse per Revolution
PW	Pulse Width
PWM	Pulse Width Modulation
OCC	Operation Control Centre
TTL	Transistor-Transistor Logic
VOBC	Vehicle On-board Controller

CHAPTER 1: INTRODUCTION AND LITERATURE REVIEW

1.1 INTRODUCTION TO COMPUTER-BASED TRAIN CONTROL SYSTEMS

A recent analysis of automatic train control (ATC) market trends revealed increasing interest and demand from the mass transit authorities to operate driverless lines (Braban, 2007). This preference concerns not only new lines, but also upgrades to the existing driver-based lines. From a technology point of view, the communications-based train control system (CBTC) has been proven to be the best solution for driverless operations. It contributes to increase operational flexibility and to reach high safety, reliability and availability targets with a low life cycle cost.

At the design level, a top-down system approach is necessary to obtain the desired performance and cost. Indeed, there are key system issues to consider when a CBTC system substitutes for the driver, particularly to perform the safety critical functions such as authorizing train safe departure, safe stopping and other train motion managements, in case of degraded operational conditions.

As defined in the introductory section to the IEEE P1474.1 (McGean, 1999), the CBTC system has been designed to overcome the fundamental limitations of conventional track circuit-based systems and therefore it permits more effective utilization of the transit infrastructure. Its basic characteristics include:

- Determination of the train location, to a high degree of precision, independent of track circuits.
- A geographically continuous train-to-track and track-to-train data communications network to permit the transfer of significantly more control and status information than is possible with conventional systems.
- Wayside and onboard vital processors to process the train status and control data and provide continuous automatic train protection (ATP); automatic train operation (ATO) and automatic train supervision (ATS) functions can also be provided.

A CBTC system for driverless operation means designing an automatic train control system that substitutes for the driver. This gives the main assets of the CBTC for the driverless train operation that will be discussed in the next section for the automatic train traction control system.

Any CBTC system is equipped with ATP and ATO subsystems. The fundamentals of ATP and ATO are the train traction control along with propulsion and braking. Figure 1-1 represents an illustration example of the braking curve with regarding to speed and braking rates. Benefits of CBTC technology include the economical support of automatic train operations (both on the mainline tracks and in maintenance depots), improved reliability and safety, and reduced maintenance costs through a reduction in wayside equipment and real-time diagnostic information.

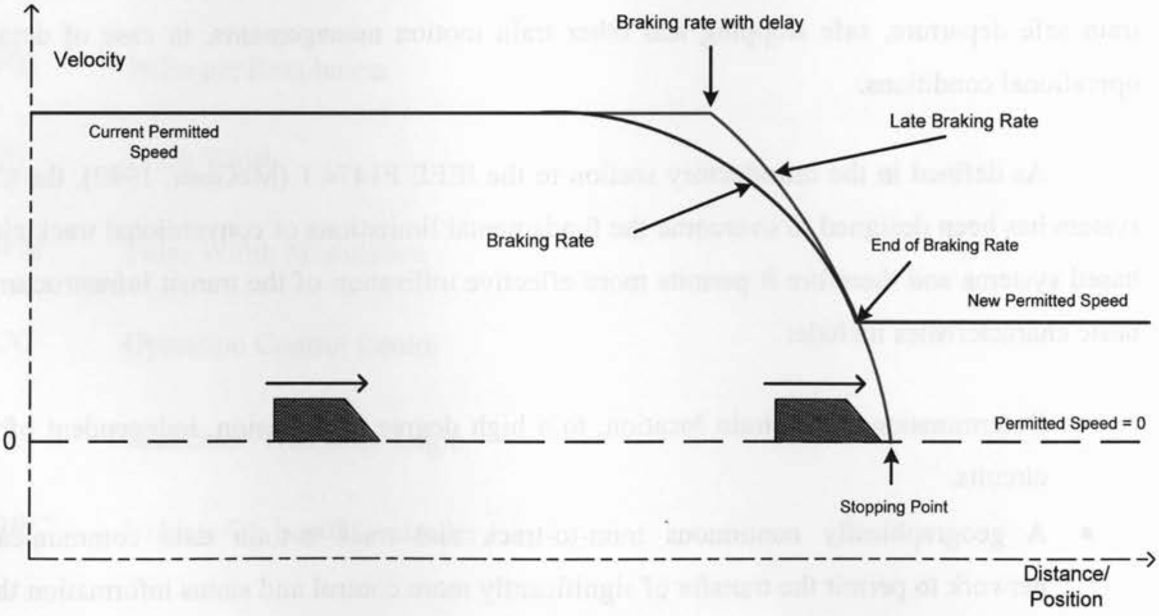

Figure 1-1: Train Motion Supervision in a CBTC System

Figures 1-2 is a visual representation of a vehicle interface with all related components to control the train motion. These components are Propulsion, Brake and Slip/Slide control. Due to the safety critical aspect of rail industry, the fail-safe model is chosen for the industry. Fail-safe describes a system which, in the event of failure, responds will cause no harm or at least a minimum of harm to other devices or danger to people. Fail-safe components of a system do not allow a certain improper system behavior, although some proper behaviors are impeded. For example, if traction condition is in slip/slide condition for certain period of time, the condition is considered as failure, but it may be considered fail-safe if its failure does not let the train to continue to the uncertain position that may cause physical accident. In contrast, a fail-safe traction condition will remain in slip/slide during a failure, but cannot be in normal condition at the same time even if the system tries to correct it.

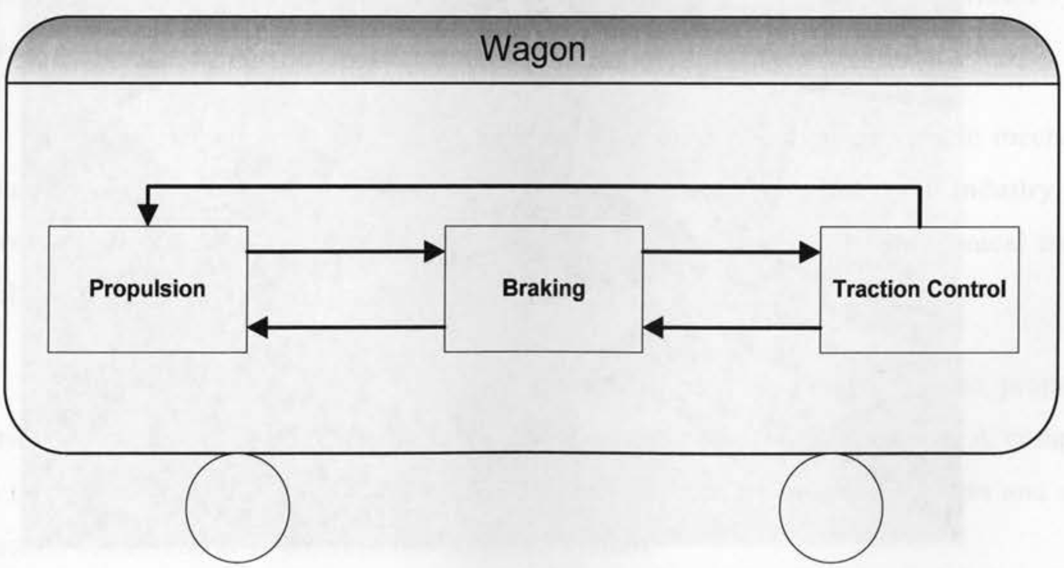

Figure 1-2: A Block Diagram of a Train Traction Interface

Furthermore, the CBTC technology allows cost-effective upgrading to a higher system performance by overlaying components onto an existing ATC system. Availability of the CBTC system is a fundamental issue for driverless train operation as such train traction control subsystem is the heart of the motion system to achieve the availability target of 99.998%. All availability and headway can be calculated and scheduled in ATS subsystem. Figure 1-3 is an example of operation control room (OCC) for train positioning management and traffic monitoring. Normally, in the control room the operator monitors the train location, scheduling, routing and other aspects of the system operation, like hazard and catastrophic conditions.

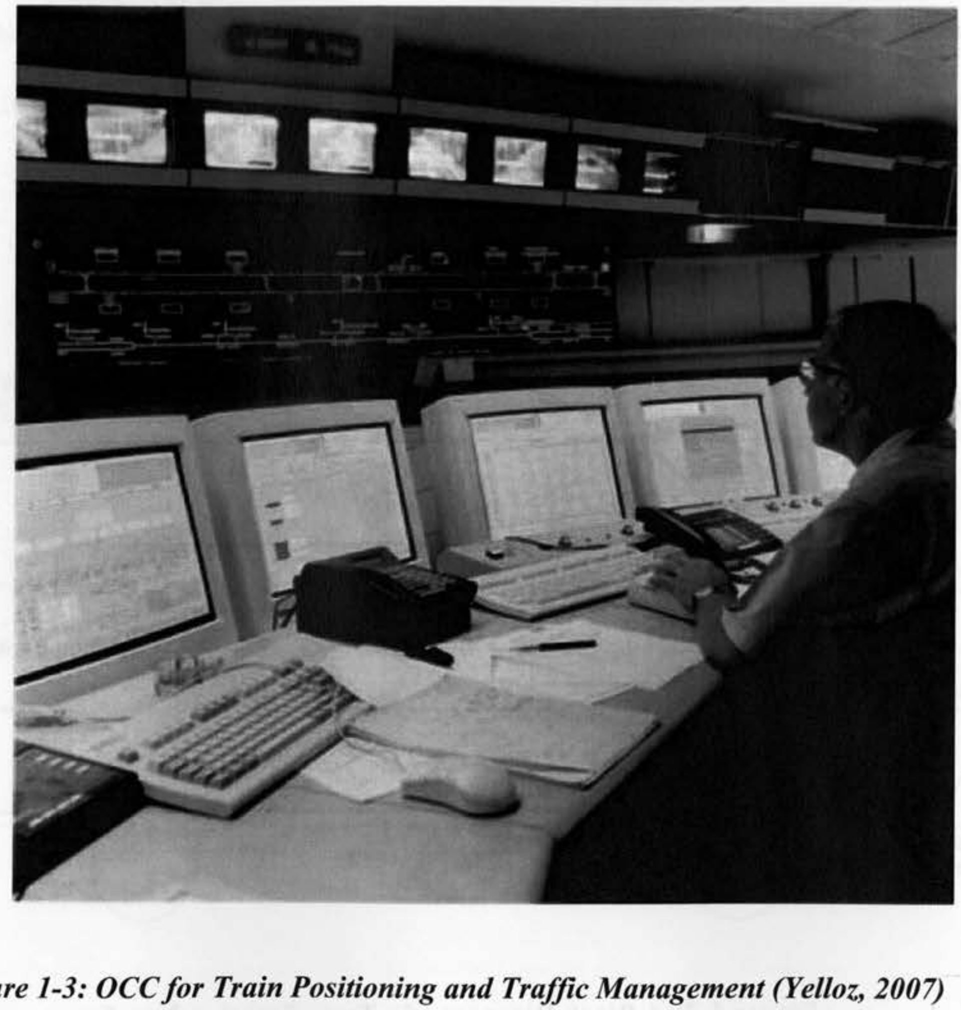

Figure 1-3: OCC for Train Positioning and Traffic Management (Yelloz, 2007)

1.2 INTRODUCTION TO TRAIN TRACTION CONTROL SYSTEMS

In attended-train operation, the driver sits in the front cabin of the train observing the track, detecting potential sources of collision and stopping the train in case of a hazardous situation. Traction acceleration and braking deceleration can be controlled by the driver or by the ATO under the supervision of ATP. The speed is supervised continuously by ATP under the speed profile and the events. Under the control of the ATP and ATO, the train stops automatically in station and any other stopping points (target points). High-performance CBTC system designed for the attended-train operation already automates most aforementioned driver functions.

The main difference between the attended-train and the driverless operation lies under train positioning (Liljas, 1997) and train motions control (traction and braking). In attended operation, the driver is in charge of the train motions and reporting position. In driverless system, the ATP and ATO are responsible for train positioning and vehicle motion control including traction and braking. Therefore and in order to control positioning and motion of vehicles in such an integrated system, a sub-system is needed to control these safety aspects, namely known as The *Train Traction Control System*. This system is considered as a safety vital critical system and is dealing with the train safe departure, safe stopping and the safe train separation.

The traction control system in the rail transit is an application of vehicle mechanical motion, sense of motion, and detection/control of traction conditions. In the rail industry, there are two different approaches to the traction control systems namely; the mechanical traction control and the computer-based traction control.

Mechanical traction control is the vehicle oriented and utilized by the propulsion (electrical motor and engine), braking and other electromechanical components. A computer-based train traction control system includes three sub-components to sense, process and adjust the traction conditions in a vehicle in an integrated system.

1.2.1 BASIC CONCEPTS

The train traction control in the railway is subject to longitudinal forces due to t number of train related dynamics including the braking and traction. These longitudinal forc affect the dynamics of vehicles in a complex manner. The severe braking or traction may affe the safety and stability of vehicles adversely.

Therefore, there is a need to study the vehicle dynamics as a function of longitudin forces with a view to minimize the risk to railway transportation. The following sections discu the necessary conceptual elements that are used in train control system along with rail ar vehicle dynamics.

1.2.1.1 Axis System

There is a coordination system in a vehicle with six degree of freedom. The linear motic along the X, Y, Z axes are termed as longitudinal, lateral and vertical translation, respectivel Rotary motions around X, Y and Z axes are termed as roll, pitch and yaw, respectively.

1.2.1.2 Vehicle and Track

Each vehicle consists of three main parts as vehicle (wagon), wheel sets and drive axe (bogies). Typically drive axels of vehicle has three parts; beam, wheel axels and suspension.

The track is one of the most important elements in the railway operation. Its ma function is to provide guidance for the vehicles in addition to supporting the running train ar absorbing the heavy mass and induced vibration. The track has a complex structure with elast and solid properties.

1.2.1.3 Wheel Set

A wheel set normally consists of two wheels attached to one drive axel. These wheels ca or cannot be independent. Each vehicle manufacturer determines the wagon dynamics ar configures the characteristics of such a wheel set. There are at least two wheel sets per wagon i a train. The dynamic characteristics of a railway and vehicle are defined by the interactio between the wheel set and the rail. The vehicle movement along the rail or track is the most fundamental factor that affects the vehicle dynamics. The connection between wagon and wheel set are handled by suspension and other mechanical joints and stabilizers. Figure 1-4 depicts a railway wheel set positioned on the track.

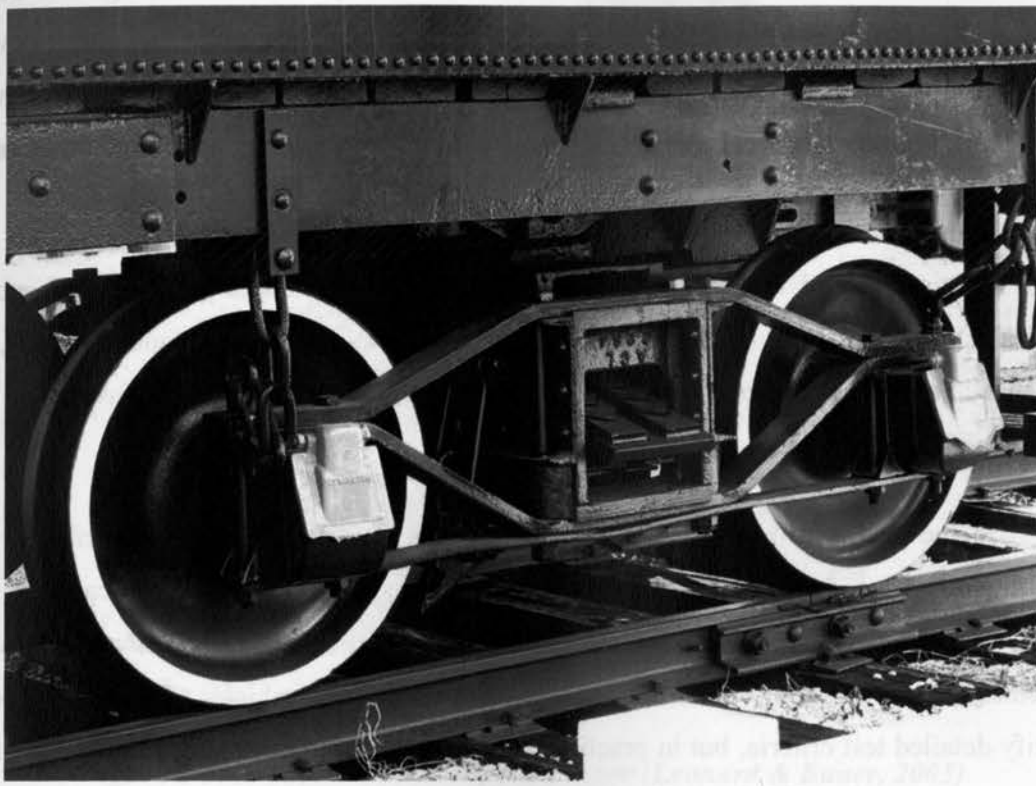

Figure 1-4: A Wheel Set on the Rail Track (Wikipedia, 2007)

1.2.2 SPEED SENSORS

In computer-based transit system the traction controller is monitoring the vehicle's driving condition in conjunction with the wheel condition. In which, there are three main components, namely, the *sensors* (speed sensor, accelerometer, tachometer), *controllers* (microcontroller, microprocessor), and *actuators* (propulsion, transmission lines, engine). The sensors provide the controllers with the information about one or more vehicle operating state of natures such as: train speed, train travel distance, travel direction and train acceleration, wheel speed and wheel acceleration, torque, etc.

The controllers process the detected information to determine the presence of wheel traction conditions (i.e., slip/spin, normal and slide) and output a command signal to control the actuator for limiting wheel differential. The actuator includes one or more devices for accomplishing such tasks as: braking individual wheel, restricting differentiation between the drive axels, limiting electrical propulsion output power, and engaging additional drive axels etc.

Many systems in a rail industry have sensors, such as vehicle or locomotive, in some cases sensors are used to measure the wheel speed or the changes in the wheel speed. This applies in particular to the traction control, and to protect wheel condition such as creep, jerk and slip/slide. These tasks are performed by a number of rotary speed sensors that can be found in various parts of the vehicle.

In the past, sensors for this purpose often failed to function satisfactorily or were not reliable enough and gave rise to the vehicle faults. This was particularly the case for the early mainly analogue sensors, but digital models were also affected. This was mainly due to the extremely harsh operating conditions encountered in the rail vehicles. The relevant standards specify detailed test criteria, but in practical operation the conditions encountered are often even more extreme (such as shock, mechanical vibration, and electromagnetic interference).

Each speed sensor generates pulses that represent wheel rotation resulting from train movement at certain speed and acceleration. The pulse width, pulse count and pulse phase shift are the three features that are generated by the speed sensor and are used to measure the wheel speed, wheel travel distance, wheel travel direction over the defined application cycle time (e.g. 100 ms). In fact pulse width represents *speed*, pulse count represents *distance* and pulse phase shift represents *direction*. Figure 1-5 is an example of a tooth wheel speed sensor, which can be used in any vehicle in transit system. The pulse width is the width of the pulse in time unit and pulse count is the number of pulses in time unit as shown in Figure 1-6. Also pulse phase shift is the difference and order of the two phases, each phase comes from a channel of the pulse modulation in dual channel speed sensors which is widely used in such application.

Figure 1-5: A Tooth Wheeled Speed Sensor (Leonard & Bauer, 2005)

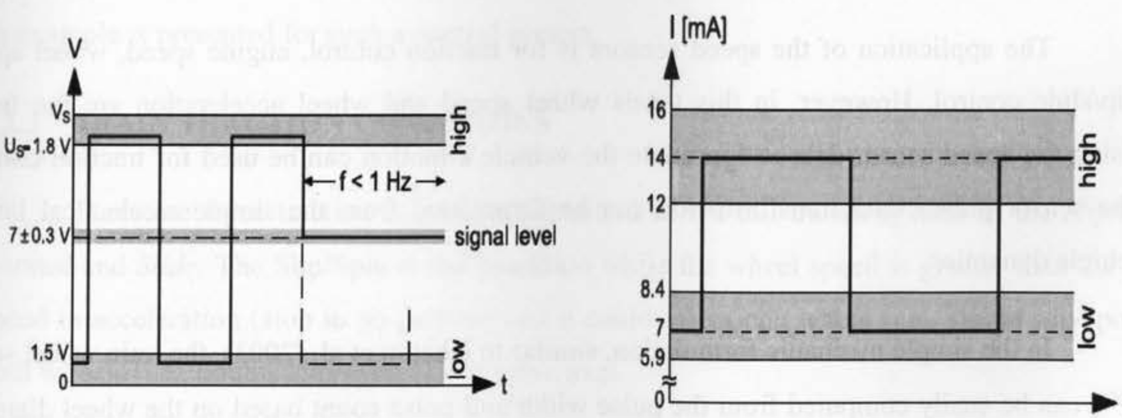

Figure 1-6: Speed Sensor Output Graph (Leonard & Bauer, 2005)

As depicted in Figure 1-7, the wider the pulse width is the lower the speed. In other word, the slimmer the pulse width is the higher the speed. Pulse count is also affect the travel distance which means higher the pulse count is higher the travel distance. All electrical and mechanical characteristics for a speed sensor can be found in Leonard & Bauer (2005). These characteristics are used to configure a sensor base traction control system.

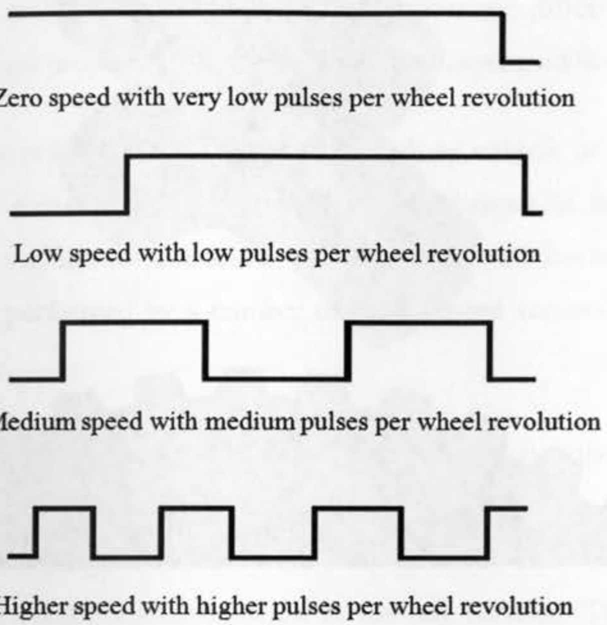

Figure 1-7: Speed Sensor Pulse Width Patterns

The application of the speed sensors is for traction control, engine speed, wheel speed, slip/slide control. However, in this thesis wheel speed and wheel acceleration are the focus. Using the speed sensor data to formulate the vehicle's motion can be used for traction control. The sensor pulses data transformation can be formulated from the simple mechanical law in vehicle dynamics.

In the simple mechanic formulation, similar to Khatun et al. (2003), the train wheel speed (V) can be easily computed from the pulse width and pulse count based on the wheel diameter given in Equations 1-1 and 1-2:

$$V = \frac{(\pi \times \theta_{wl})}{(\upsilon_{pw} \times \psi_{ppr})} \tag{1-1}$$

Similarly, the wheel traveled distance (D) can be calculated from the pulse count.

$$D = \frac{\kappa_{pc} \times (\pi \times \theta_{wl})}{\psi_{ppr}} \tag{1-2}$$

Traction condition is defined by comparison of the wheel speed (from speed sensors) vs. the train speed and train acceleration over the defined application cycle. The accelerometer is also used for the cross check and plausibility check among the sensors. In fact, the accelerometer is responsible for providing the acceleration value to be used in cross referencing (i.e., plausibility, validity) of speed sensor data.

This system is considered a real-time system that is designed to calculate the speed, acceleration and distance over the time (application cycle). On the one hand, the speed is the delta distance over the cycle time and on the other hand the acceleration is the delta speed over the same cycle time. The traditional traction control system in each vehicle has at least two speed sensors (for reliability and redundancy) and one accelerometer (for safety and cross check) and traction module is the combination of all hardware components along with the real-time software application to conduct the traction detection. In the next section, train tractions are described and an example is presented for such a control system.

1.2.3 TRAIN TRACTION CONDITIONS

There are three traction conditions identified in the rail transit system as the *Slip/Spin*, *Normal* and *Slide*. The Slip/Spin is the condition while the wheel speed is greater than the train speed in acceleration (stop to go pattern) and it could affect one wheel (i.e., single slip/spin) or both wheels (i.e., double slip/spin) in one drive axel.

The normal traction condition that the wheel speed is either equal within the tolerance (likelihood) of train speed and it is the most desirable condition because there is no impact on motion and service of the vehicle in the revenue service. The slip traction condition introduces wear out of the wheels and it makes unreliable drive condition for a train with the worn wheels. The slide traction condition is the condition that the wheel speed is less than train speed (go to stop pattern) and it could affect one wheel (i.e., single slide) or two wheels (i.e., double slide) in one drive axel. The slide traction condition introduces uneven wear out of the wheel that causes wheel vibration and makes unreliable suspension and driving condition.

The slip or spin and slide traction conditions are both causing impact on the vehicle's positioning and safety in an integrated system and it can compromise the safety, reliability, maintainability, and availability of the vehicle over the track and vehicle specially if there are passengers on-board.

The slip and slide are the same phenomenon in the opposite direction, which means slip happens when the train accelerates and slide happens when the train decelerates (brake). In the classification model, the normal traction and the slip-or-slide condition are depending on the acceleration or the deceleration.

The following criteria are identified under the train traction control systems and any application whether modern or traditional should take it into the account the effect of the following elements in design and application:

1.2.3.1 Vehicle Stability

In the vehicle stability concept, hunting and curving are the challenges between the suspension and friction between wheel and rail in straight or curving tracks. Suspension of wheel set could be made stable up to any required critical speed. The stability theory was used to design the suspension for a vehicle that was successfully introduced for Shinkansen high speed train in 1964 in Japan.

1.2.3.2 Creep Factor

In this theory, the wheel-rail contact forces can be determined and the equations of motion that describe the wheel set dynamics can also be derived. Creep is the condition that the vehicle is either in slip or slide (IEEE, 1999). The Creep force or creepage was first defined by Carter (1926) who was concerned with the action of the locomotive wheels when the large amount of tangential forces were transmitted during the acceleration and braking. Carter has shown that the difference between the circumferential velocity of a driven wheel and the translational velocity of the wheel over the rail has a non-zero value as soon as braking or traction couple is applied to the wheel.

The difference increases if the braking or traction couple increases, which means that there exists a relationship between the couple and the velocity leading to saturation when the friction maximal value is reached (slip/spin). The only problem with Carter's method is the focus is on longitudinal force which is not sufficient for the vehicle dynamics with lateral movement.

1.2.3.3 Wheel Traction

Traction, in general, can be viewed as the reverse process of braking. From this point of view, all parameters that influence the dynamics of wagon during braking can also affect the dynamics of wagons during traction. However, most of the wagons are not self-propelled. To accelerate, they get pulling or pushing forces from a locomotive.

The traction forces in a locomotive are usually generated by diesel engine or electric traction motors that produce torque transmitted to the wheel set axels using gear box, whilst the wagon receive the traction force through pulling or pushing action of the mechanical couplers.

Slide factors and controlling the skidding include ice, oil, water, leaves, sand, etc. The slip percentage and wheel-rail friction are also important in any slip control. Figure 1-8 depicts the adhesion force against velocity. In fact the function of adhesion force on vehicle slip velocity has two different thresholds for wed and dry condition. The adhesion force is higher for dry condition with lower slip velocity and similarly for wet condition adhesion force is lower with higher slip velocity.

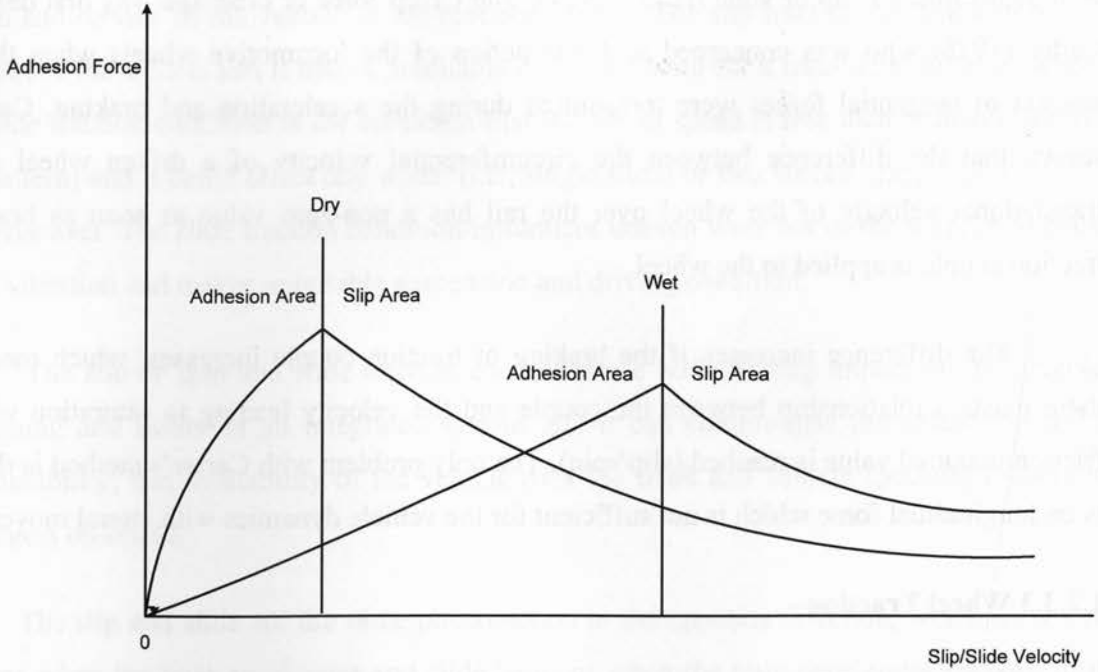

Figure 1-8: Adhesion Force vs. Slip Velocity

Equation 1-3 represents the slip/slide factor with regard to wheel speed and train speed. In which if $V_{car} = V_{wheel}$ the train is in normal condition otherwise the train is in slip/slide. If $V_{car} > 0$ and $V_{wheel} = 0$ then the train is in absolute slide condition. In general the sign of the slip/slide factor is giving the condition, as such if $V_{car} > V_{wheel}$ the train is in slide otherwise the train is in slip condition ($V_{wheel} > V_{car}$).

$$S = (V_{car} - V_{wheel}) / V_{car} \tag{1-3}$$

In his model, the friction coefficient between the wheel and the rail is considered as a function of the slip of the wheel which is formulated accordingly. This design also used to design a control system that would prevent the slip during traction of an electric motor coach. Figure 1-9 shows the slip/skid areas which are the left side and right side of the grey area. In fact the grey area shows ample adhesion that vehicle performs normal traction with no slip or no skid (slide). The nature of the slip and slide is the same, except for the sign of the acceleration. On the other hand, slip happens in acceleration (traction) and slide happens in deceleration (braking).

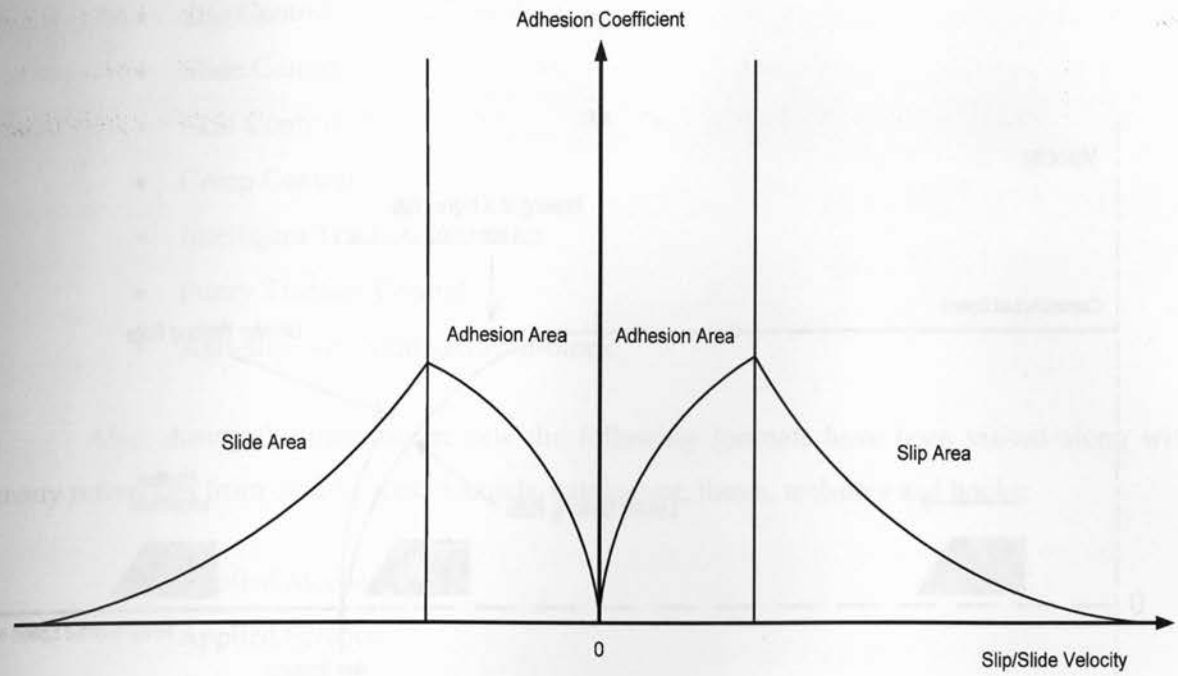

Figure 1-9: Adhesion Area with Respect to Slip/Slide Velocity

1.2.3.4 Safe Braking Model

Figure 1-10 shows safe braking model for better positioning along with train safe separation. All acceleration and braking should be followed under section 5.9 of IEEE 1475 (1999). In this figure, the safe braking model is presented to make sure a train at its maximum possible speed can stop in the target point including all position uncertainty, maximum acceleration/speed and braking curve rate. This means, a train should follow the safe braking curve until it stops in a safety distance from the approaching train (safe separation). In this model, if a train for any reason is in the traction condition for the certain period of time and the system does not detect/control the condition, then the position uncertainty will grow in such a way that the train separation will be in hazardous condition. This is leading the train to be in an accident situation.

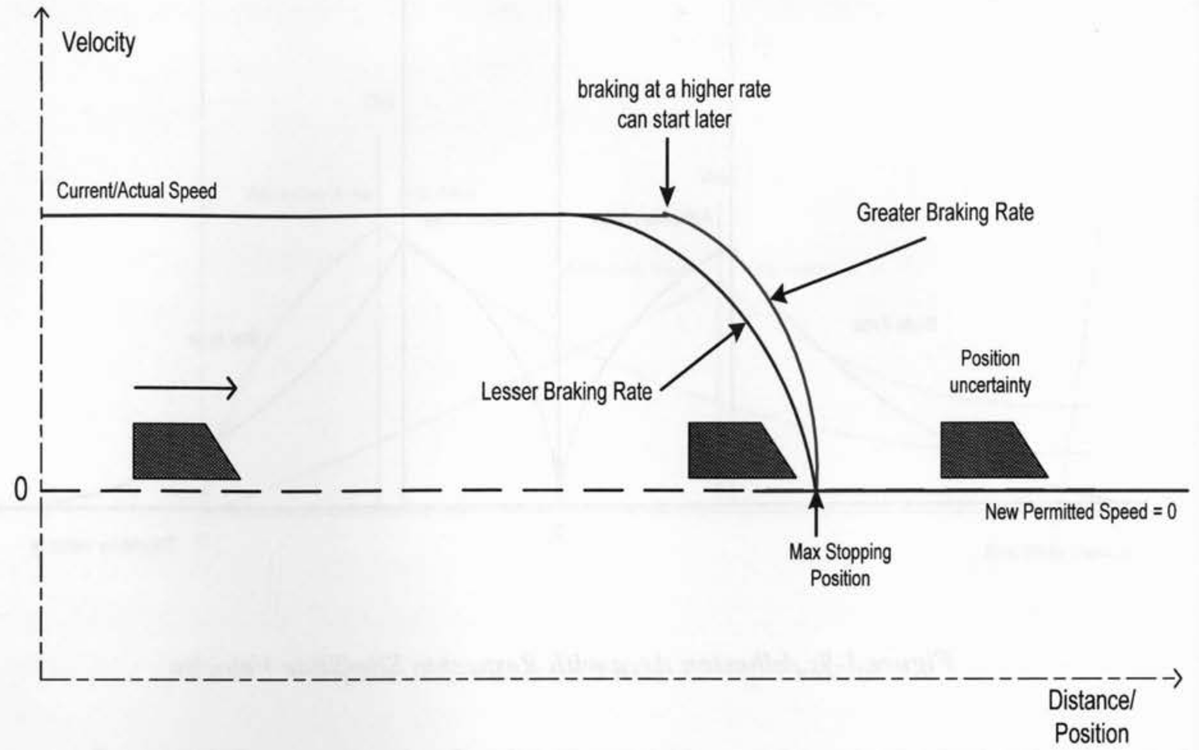

Figure 1-10: Safe Braking Model for Safe Traction and Safe Separation

1.3 LITERATURE REVIEW

The train traction control system is one of the areas which have been automated to maximize the safety, reliability and minimize the processing errors to have a better motion during the system operation cycle. The following sections introduce the research area for traction control systems that has been done to complete the thesis study. The author has reviewed more than 200 papers in traction control systems, in which, 90 papers have been chosen for literature review. The following keywords have been used to search the criteria as follows:

- Train Traction Control
- Rail Traction Control

- Slip Control
- Slide Control
- Skid Control
- Creep Control
- Intelligent Traction Control
- Fuzzy Traction Control
- Anti-slip, Anti-skid and Anti-block

Also, during the literature review the following Journals have been visited along with many references from conferences, manuals, catalogues, thesis, websites and books:

- Applied Mechanics
- Applied Science
- Automatica
- Electrical Engineering in Japan
- Elsevier Science Publisher
- Fuzzy Sets Systems
- IEE Proc. Electrical Power Application
- IEEE Transactions on Fuzzy Systems
- IEEE Transactions on Industrial Electronics
- IEEE Transactions on Industry Applications
- IEEE Transactions on Neural Networks
- IEEE Transactions on Power Delivery
- IEEE Transactions on System Management and Cybernetics
- IEEE Transactions on Vehicular Technology
- Information and Control
- Japan Railway and Transport Review
- Journal of Engineering for Industry
- Journal of Rail and Rapid Transit
- Power Engineering Journal
- Railway Safety

- The International Journal of Robotics Research
- Vehicle System Dynamics
- Vehicle System Dynamic Supplement
- Wear

1.3.1 VEHICLE TRACTION STUDIES

The dynamic behavior of the vehicle had known since the early years of the railway history. The kinematic oscillation and its stability problem had been studied in the track dynamics (Marshal, 1938). The first mathematical relationship for this kinematic oscillation and relationship between wavelength and wheel set dynamics had been introduced and improved by Klingel (1883) and Redtenbacher (1885), respectively.

The theory of creep was introduced by Carter (1926). Gilchrist (1998) had reviewed the history and the development of the research on the optimization of the hunting (stability) and curving (banking) problems. Matsudaira (1952) was the first to solve the complexity of the wheel set equation of motion and concluded that through proper design. Following Matsudaira's work, from the mid fifties until the mid sixties, most of the researches on railways vehicles dynamics were focused on the subject of stability (de Pater, 1961 and Wickens, 1955-6).

More extensive study on the vehicle dynamics came after Kalker (1973) who studied the rolling contact to calculate forces generated in wheel-rail contact patch. Kalker's method is widely used due to numerical approach through computer modeling. Rinehart (1978), Tuten et al., (1979), Renger (1983), de Pater (1989), Ahmadian (1998), Yabuno et al. (2001), Anderson et al. (2002) and Mohan (2003) continued working on the wheel-rail stability via different methods and improvements.

Although this section (and also the next section 1.3.2) of the literature review is not directly related to the thesis, but it is necessary to review papers to get to know the state of the knowledge in train traction control in the academic aspect.

1.3.2 WHEEL TRACTION STUDIES

Vermeulen and Johnson (1964) proposed a creep-force law, which included the longitudinal and lateral creepage. Further elaboration in the creep formulation is presented by Garg and Dukkiapati (1984), Dukkiapati (2000), Johnson (1985) and Andrews (1986). The most successful method of calculating the creep force is presented by Kalker (1973) who then wrote the computer program to calculate it. In 1991, Polach (1999, 2001 and 2005) also improved and simplified the Kalker's method.

Kalker (1991) has provided a very good presentation on the wheel-rail interaction forces. Details of the mathematical analysis on rolling contact phenomenon can be found in Jacobson and Kalker (2000). Malvezzi et al. (2003) carried out an investigation of the braking in trains.

Slide factors and controlling the skidding are elaborated by Macfarlane (2000). The slip percentage and wheel-rail friction are elaborated by Ohishi et al. (2000). Muller and Kogel (2000) have presented the Roll-Slip control.

Balas (2001) developed a model for the sliding wheel of a railway car during braking. This design also used in Ohishi et al. (2000) to design a control system that would prevent the slip during traction of an electric motor coach. Independently, Cocci et al., (2001) developed a similar model to Balas.

1.3.3 POWER TRACTION STUDIES

Currently, most of the existing traction control systems are vehicle oriented and they are the application of mechanical vehicle dynamics along with the wheel-rail traction. The existing rail traction controllers are using electrical and/or mechanical sensors or devices to detect and maintain the conditions (Chan, 1990; Hill, 1994, 1995 and 1996; Goodman, 1997; Shen and Butterworth, 1997; White, 1997; Goodman et al., 1998; Chan, 1998; Bennett et al. 1999; Chang et al. 2004; Steimel, 2004; Mariscotti and Pozzobon, 2004 and 2005; Kulworawanichpong and Goodman, 2005; Shimizu et.al., 2007).

These research studies consider the traction as an application of electrical propulsion along with pulse width modulation (PWM) control and torque mitigation. These components can be controlled through the logic circuit, track circuit and power lines. Also, the electrical and power applications of the tractions can be sensor-based and/or controlled by an embedded computer. These systems are considered the hard real-time and working in the very low application cycle (e.g. 10 ms).

Embedded traction control processors are mainly independent and have no intrusive interaction with the central computer due to the fast action of the module and slow communication. Power traction control is necessary for railway signalling; however, according to the mentioned studies, there is still no connection through the integrated system under ATP and ATO. Some idea of the thesis is from this section of literature review, in regards to artificial intelligent and fuzzy model that is discussed in the next section (1.3.4).

1.3.4 MODERN TRACTION CONTROL STUDIES

Modern traction controls have become very popular in the last few years (Lee, 1990; Cheok and Shiomi, 2000; Hiroaki et al., 2001) due to the ability of the new methods to address the uncertainty, learning ability and adaptability. Since slipping/sliding is an uncertain non-linear, time varying process, a non-linear controller may be well suited. This is one of the reasons why intelligent logic is interesting when it comes to slip/slide control such as artificial intelligent, probabilistic or fuzzy. A few different ways of using a modern controller to control slipping/sliding have been encountered during literature review.

Chan (1990) introduced an artificial intelligent method for processing and simulation of traction control model. He showed how artificial intelligence is taken to account for rail industry. Also, Bennet et al. (1999) introduced a method to address the fault tolerance of the sensors in speed sensor and traction control systems. Although both models are traction related, but both models are considered as component driven solutions rather than system driven model than can be controlled by ATO and ATP.

In 1997, Garcia-Riviera et al. introduced a fuzzy approach for anti-slipping train traction control and later in 2000; Cheok and Shiomi studied the fuzzy logic in traction control and antiskid as well. Frylmark and Johnsson (2003) studied several methods of the slip control such as adhesion observer based controller, the fuzzy logic slip controller and hybrid slip control method. They proposed few improvements to the existing traditional models. The most of the methods are the application of mechanical/electrical component and cannot be part of an integrated system like CBTC under supervision of ATP and ATO.

Based on the above literature reviews along with system characteristics and sensor configuration, the following items in a modern traction control are suggested:

- Sensors Signal: Sensors generate electrical pulses and pass it on the I/O card,
- Signal Filtration: Input signal is filtered (low pass filter) to remove noises,
- Data Conversation: The filtered signal is converted, the outcome is data,
- Wheel Data: All converted data are the wheel data (e.g. wheel speed),
- Train Data: All wheel data are converted to the train data (e.g. train speed),
- Plausibility: All measured data have to be cross checked and plausible, and
- Traction Control: Upon plausible data, traction condition is controlled.

Normally, the sensor outputs are pulse phase, pulse width and pulse count, which will be converted to the wheel travel direction, wheel travel distance and wheel speed, respectively. Once the wheel data are measured, the train data are conducted into train travel direction, train travel distance and train speed. In order to the data be trustable, the plausibility check is performed among the sensors. As a result of the above process, the traction conditions are conducted into slip, normal and slide, as long as the condition persists. For more procedural view, please refer to the Figure 1-11.

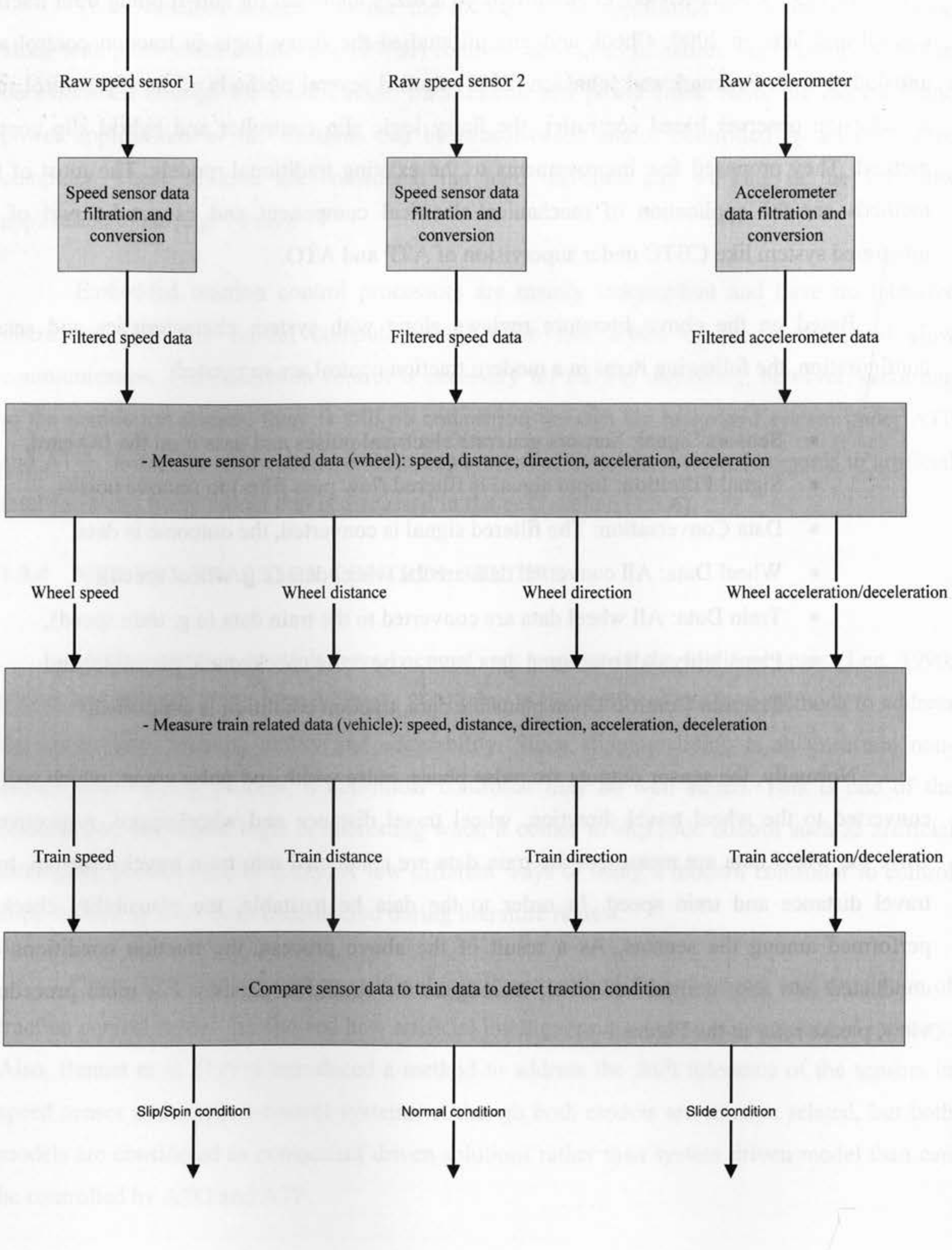

Figure 1-11: Traditional Train Traction Control

1.3.5 SUMMARY AND SHORTCOMINGS

Despite the extensive researches which are mainly focused on traction and its mechanical aspect, still there is not much integrated computer-base systems available that can monitor the traction condition in an ATC under the ATP, ATO, and ATS supervisions. This thesis studies approaches to the concept from fuzzy, probability and motion pattern points of view, along with the vehicle characteristics, which are either not seen or less researched in the reviewed studies

The main shortcoming of such systems is that they cannot be monitored via a central computer for motion and position management in a CBTC system due to the safety concern of vehicle motion and train safe separation. Most of these shortcomings are considered system related and can be seen as elements of management of the transit system. Hardware and component base traction control which are common solution for vehicles are still necessary for such a system, however this thesis is the complementary of the mechanical aspect of the traction. Some of these shortcomings are addressed by the thesis study that will be discussed in the next sections.

In order to have a better picture of what has been done and what are the coverage criteria of the studies, Figure 1-12 depicts the research statistics (number of papers) in this thesis study for a total of 90 reviewed papers. In fact, the reviewed papers are categorized into two main sections, the traction systems (vehicle traction, wheel traction and power traction) and the traction models (intelligent, fuzzy, and probabilistic).

The traction systems is the main category with 78% of the total reviews, and the traction models comes along with 22%. Even though the traction systems has a portion of 78%, but only power traction with 22% is somehow used for the thesis plus another 22% form traction models. This means, 44% of the literature reviews somewhat elaborates the state of knowledge of modern and intelligent traction control systems. The rest of the reviews are here for witness to diversity of the traction control along with historical approaches in the industry.

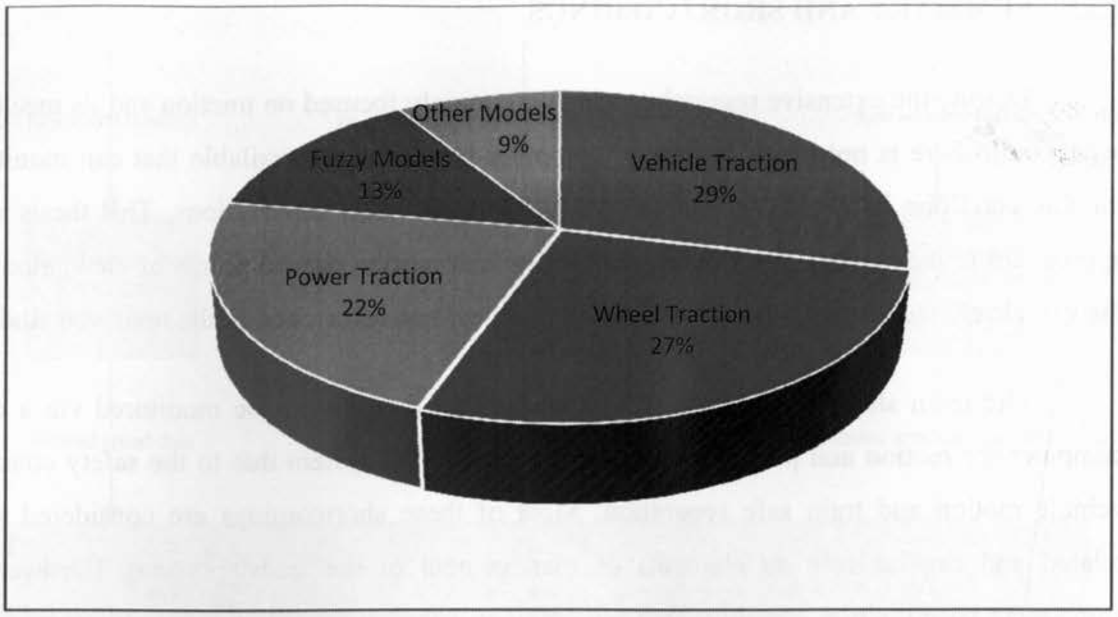

Figure 1-12: Statistical Report on the Researched Studies

It has been observed during the research studies and literature review that traction control has been categorized in the industry into few sections as showed in Figure 1-12. In this regard, Table 1-1 shows the coverage criteria of the traction control and characteristics of the existing industry systems. This table represents the shortcomings of the existing systems vs. the proposed models that cover all criteria.

Industry Section	*Electrical*	*Mechanical*	*Sensors*	*Vehicle Pattern*	*CBTC*
Vehicle Traction	Yes	Yes	No	No	No
Wheel Traction	Yes	Yes	Yes	No	No
Power Traction	Yes	Yes	Yes	No	No
Fuzzy Models	Yes	Yes	Yes	Yes	No
Other Models	Yes	Yes	Yes	Yes	No
Proposed Models	Yes	Yes	Yes	Yes	Yes

Table 1-1: Comparison of the Industry Traction Control Systems

Basically, sensors are necessary for any control systems. Traction control in transit systems is not excluded from this fact. As such the thesis focuses on the speed sensor-based vehicle traction control systems. Therefore, knowing the shortcomings of the tradition sensor base traction control is the objective of this section. There exist several drawbacks in the traditional sensor based traction system mainly due to the existence of noise in sensors, lack of vehicle characteristics patterns and high cost of processing time (persistency, delay). These drawbacks are identified as follows:

- Real-time data dependency rather than vehicle behavior dependency,
- Sensors can detect noise and its data availability and integrity are low,
- Sensor's persistency limits the processing of the speed of traction detection,
- Sensor's noise detection delay in processing and higher tolerance,
- Higher tolerance in the traction detection introduces lower precision,
- Needs to have multiple sensors for better reliability and precision,
- Traction model does not follow any pattern and is very complex,
- Train characteristics do not affect the model effectiveness and efficiency,
- Traditional systems have high implementation cost due to the iterative field tests, and
- Most of the existing traction controls work as independent component and there is no decision management is applied.

In fact we need a modern and intelligent method that not only covers the shortcomings but also introduces a novel computational method executable in any computer-based system either on-board or embedded that can be integrated in a CBTC system. The intelligent system is very effective to cover most of the shortcomings of the legacy and existing systems that are listed above. Some of suggested improvements are listed below:

- Vehicle characteristics should be engineered in design phase rather than field experiment,
- Vehicle characteristics should be included in vehicle's motion pattern,
- Training samples should be collected from field test or simulated in lab,
- Intelligent model should be simple and easy to implement,

- Intelligent model should be generic that can be used with any sensors,
- Intelligent model should be compatible with existing sensors,
- Intelligent model should be precise,
- Unlike traditional models, the noise does not mislead the model, and
- Unlike the traditional models, tolerance and persistency are low.

1.4 THESIS OBJECTIVES

Even though the traction control system in the rail industry has been introduced for over a decade now, computer-based intelligent application of such a safety critical control system is still awaited due to the challenges faced in terms of systematic mechanical motions, vehicle characteristics and inadequate experimental studies in this area. The main aim of this thesis is to study an intelligent traction safety model in the rail industry and establish the model efficiency in terms of precision (traction detection and traction classification) to achieve safety standards for traction control system.

1.5 THESIS STRUCTURE

In chapter 1, computer-based train control systems and train traction control are introduced; along with basic concept of wheel-rail, speed sensor and traction conditions. The thesis objectives and thesis overview are also presented. In chapter 2, the Bayesian model is discussed, along with discussion of an experimental example. In chapter 3, the fuzzy model is discussed, along with discussion of an experimental example. In chapter 4, the conclusion and future work are discussed.

CHAPTER 2: BAYESIAN TRACTION CONTROL SYSTEM

2.1 INTRODUCTION

The main purpose of the proposed Bayesian intelligent model is to recognize traction patterns and to classify motion inputs into the learned tractions. Most of the traction system applications are focusing on the motion of the wheel and train traction along the axels (Sladover, 1991; Gillespie, 1992; Swaroop and Hedrick, 2001; Khatun et al. 2001). In rail transit systems, due to the limited motion dynamism, the Bayesian decision theory can be applied for the benefit of safety and reliability to alleviate service interruptions during revenue service.

As mentioned in the literature review section (1.3), some of the new methods have already been applied (Khatun et al. 1999; Hiroaki et al. 2001); however, still the applications are complex and far from computability and they have no knowledge of the vehicle characteristics, (Lee, 1990; Wang and Mendel 1992; Wang, 1993; Constantin, 1996; Bingham et al. 2003).

In this thesis, the focus is on speed sensor and accelerometer inputs to recognize and to classify the traction conditions in the intelligent format. In order to recognize the traction conditions (i.e., slip/spin, normal and slide), the traction patterns need to be learned in data samples. The patterns can be formulated and classified under Bayes Decision Theory, (Duda et al. 2001).

This decision theory is chosen due to, firstly, higher precision of Bayesian theory, secondly, because of manageable number of state of natures (traction conditions) and, lastly, manageable number of features (delta speed and train speed) along with availability of the prior knowledge of the state of natures. The prior knowledge can be derived from the field logs or simulated log along with knowing the vehicle's characteristics and engineering the track/vehicle behaviors. These behaviors are listed: guideway layout, jerk, max/min train acceleration, max/min train speed, weather condition and other mechanical aspects of the motion like tilt, banking, braking, weighting, etc.

Bayesian decision theory is used to model the intelligent traction detection for such a safety control system. Further elaborations will be needed to show how the traction patterns are extracted from the training data set and how traction conditions are recognized through the real-

time data. The scope of this intelligent method is on detection boundary and its decision ru
Data conversion, noise filtration, traction mitigation and motion adjustment are out of scope
this thesis and assumed to be addressed by other modules in conjunction with traction module.

The proposed model is generic and can be applied for any sensor, tachometer
accelerometer. As a configuration assumption, two speed sensors and one accelerometer are u
in this study to represent model with an example for result illustration. The accuracy of the re
in the Bayes theory model is depend on the number of training samples that include all possi
traction conditions. Training data set can be either simulated or collected from the lab or fi
tests along with knowing train characteristics such as wheel diameter, maxim
acceleration/deceleration, cruise speed, service brake rate and emergency brake rate. All tract
conditions' patterns supposed to be extracted prior to application of the model on real-time d
inputs. In the preliminary step, the real physical traction conditions (i.e., spin/slip, normal
slide) are used to extract the traction patterns.

As is well known, Bayes model works for the system with the prior knowledge in wh
state of natures and features are engineered and precisely extracted from enough train
samples. Prior knowledge is the most important part of the Bayes decision theory and should
analyzed in the training samples prior to any design and implementation of the system. Figure
1 demonstrates the process steps in a Bayesian intelligent traction control system.

The principal idea came from the domain knowledge of the author in the transportat
system along with the new design and literature review of the similar systems that have be
implemented in the industry. The proposed method is unique and is elaborated for the rail tra
industry. In fact, auto industry is leading in the intelligent traction models and research
(Sladover, 1991; Jong and Chan, 1999; and Khatun et al. 2001), because of the dynamism of
market and the economical competition.

The rail industry is slow to apply new techniques due to the high cost, safety
reliability factors along with using the old vehicles that have no traction control on them. T
existing traction control systems are addressed in mechanical form of the motion and cannot
controllable by the computer in an integrated system.

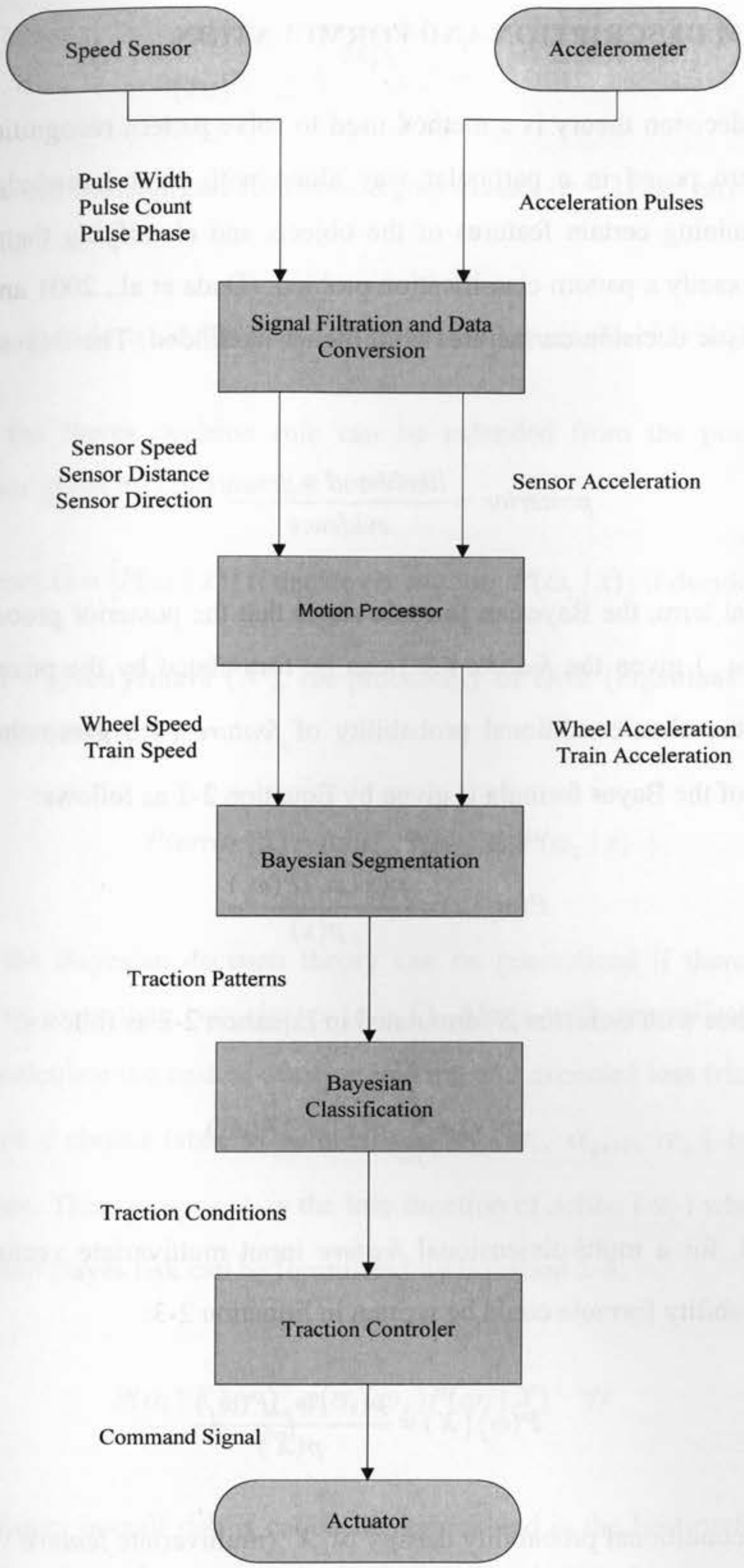

Figure 2-1: Bayesian Intelligent Traction Control Steps

2.2 PROBLEM DESCRIPTION AND FORMULATION

Bayesian decision theory is a method used to solve pattern recognition problems, when those problems are posed in a particular way along with prior knowledge. This pattern is extracted by examining certain features of the objects and classifying them using the known patterns. This is exactly a pattern classification problem (Duda et al., 2001 and Bishop, 2007). It makes a probabilistic decision on the area with higher likelihood. The Bayesian formula can be expressed by:

$$posterior = \frac{likelihood \times prior}{evidence}$$

In technical term, the Bayesian formula states that the posterior probability of a *class* or *state of nature* (ω_j) given the *feature* (x) can be formulated by the prior probability of the *class* (ω_j) and the class-conditional probability of *feature* (x) given the *class* (ω_j). The formal definition of the Bayes formula is given by Equation 2-1 as follows:

$$P(\omega_j \mid x) = \frac{p(x \mid \omega_j)P(\omega_j)}{p(x)} \tag{2-1}$$

The evidence with *c* classes is formulated in Equation 2-2 as follows:

$$p(x) = \sum_{j=1}^{c} p(x \mid \omega_j)P(\omega_j) \tag{2-2}$$

In general, for a multi-dimensional *feature* input multivariate vector $X = [x_1, x_2, ... x_d]$, the posterior probability formula could be written in Equation 2-3:

$$P(\omega_j \mid X) = \frac{p(X \mid \omega_j)P(\omega_j)}{p(X)} \tag{2-3}$$

The class conditional probability density of X (multivariate *feature* vector) is *Gaussian;* the general form of multivariate *Gaussian* density is given by Equation 2-4:

$$p(X) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp[-\frac{1}{2}(X-\mu)^t \Sigma^{-1}(X-\mu)] \tag{2-4}$$

The Bayesian decision rule for two-category classes ($c = 2$) and any given *feature* (x) is given by Equation 2-5:

$$\text{Decide } \omega_1 : \text{if } P(\omega_1 \mid x) > P(\omega_2 \mid x)\text{; Otherwise Decide } \omega_2 \tag{2-5}$$

In fact, the Bayes decision rule can be extended from the posterior probability to classification error given by Equation 2-6:

$$P(error \mid x) = \{P(\omega_1 \mid x)\text{; if decide on } \omega_2 \text{ or; } P(\omega_2 \mid x)\text{; if decide on } \omega_1 \} \tag{2-6}$$

Thus, for a given *feature* (x), the probability of error (Equations 2-5 and 2-6) can be minimized by Equation 2-7;

$$P(error \mid x) = \min\{ P(\omega_1 \mid x), P(\omega_2 \mid x) \} \tag{2-7}$$

Simply, the Bayesian decision theory can be generalized if there are more than one *feature* ($d > 1$) or more than two *classes* ($c > 2$). Along with generalization, loss function is another term to calculate the cost of decision making and expected loss (risk). Let $\{ \omega_1, \omega_2, \ldots, \omega_c \}$ be the set of d classes (state of natures) and let $\{ \alpha_1, \alpha_2, \ldots \alpha_a \}$ be the set of possible actions to be taken. Then $\varphi(\alpha_i \mid \omega_j)$ is the loss function of action (α_i) when the state of nature is (ω_j). As a result Bayes risk can be formulated by Equation 2-8:

$$R(\alpha_i \mid X) = \sum_{j=1}^{c} \varphi(\alpha_i \mid \omega_j) P(\omega_j \mid X) \quad \forall i \tag{2-8}$$

The minimum overall risk is called Bayes risk and is the best performance that can be achieved. Note that the actions are using the features to classify the state of natures. Now, the Bayesian decision can be formulated for minimum conditional risk that is given by Equation 2-9, for: i=1, 2,…, a (number of actions) and j= 1, 2, …, c (number of classes). The number c actions (decisions) should not be less than the number of classes (i.e., $a >= c$). Note that a action is part of the actuator and actuator is not discussed in the thesis model.

$$\text{Decide } \omega_j : \text{if } R(\alpha_j \mid X) = \min\{ R(\alpha_1 \mid X), R(\alpha_2 \mid X), ..., R(\alpha_a \mid X)\} \quad (2\text{-}9$$

2.3 MODEL FORMULATION

In order to apply the Bayesian formulas, the necessary features, state of natures (classes) probabilistic distribution, parameters and assumptions need to be introduced. All configuratio and assumptions are discussed in the following sub-sections:

- Configuration: Two independent speed sensors are mounted on two independent trai axels and one accelerometer is mounted on the train. Also the real-time applicatio cycle is set to 100 milliseconds.
- Features: The delta speed (x_1) and train speed (x_2) are the two features in featur vector (X).
- State of Nature (Classes): There are three states of nature (classes) as slip (ω_1) normal (ω_2) and slide (ω_3).
- Probabilistic Distribution: The Gaussian probabilistic distribution (Equation 2-4) i selected due to the nature of data and analysis is already been done on th input/sample data.

2.3.1 PRACTICAL APPROACH

The mean and variance should be calculated for each traction condition (ω_1, ω_2 and ω_3 in the training data set. In this case, Bayes decision rules are applied on the inputs to decide th traction conditions that have higher posterior probability with minimum error and risk. On th other hand, the decision boundary is the area in which the posterior probability of one conditio is greater than the other ones along with less error and risk. Because there are three states o nature (ω_1, ω_2 and ω_3) for traction conditions (i.e., spin, normal and slide), the Bayes decision rules are formulated by Equations 2-10, 2-11 and 2-12:

$$\text{Decide } \omega_1 \text{ if: } P(\omega_1 | X) > P(\omega_2 | X) \text{ AND } P(\omega_1 | X) > P(\omega_3 | X) \tag{2-10}$$

$$\text{Decide } \omega_2 \text{ if: } P(\omega_2 | X) > P(\omega_1 | X) \text{ AND } P(\omega_2 | X) > P(\omega_3 | X) \tag{2-11}$$

$$\text{Decide } \omega_3 \text{ if: } P(\omega_3 | X) > P(\omega_1 | X) \text{ AND } P(\omega_3 | X) > P(\omega_2 | X) \tag{2-12}$$

Note that, special cases like equal posterior probability among the classes will be discussed in section 2.3.3. The above decision rules can be interpreted as follows:

Decide Slip (ω_1); P (Slip | X) > P (Normal | X) AND P (Slip | X) > P (Slide | X)

Decide Normal (ω_2); P (Normal | X) > P (Slip | X) AND P (Normal | X) > P (Slide | X)

Decide Slide (ω_3); P (Slide | X) > P (Normal | X) AND P (Slide | X) > P (Slip | X)

Therefore, the above decision rules should be applied in each speed sensor data and then cross compared for plausibility purpose. To reach a decision, the prior probability and class conditional probability for the available state of nature (i.e., slip, normal and slide) and features (i.e., delta speed and train speed) are required. The patterns need to be extracted from the training set into the intelligent format. The training data set should include three columns of data that two columns are for the speed sensor 1, speed sensor 2 and the third column is for traction states conditions (ω_j where j=1, 2, 3). The third column is supposed to be the real traction condition, which is derived from the lab simulation.

In fact, training data set should be simulated to include all aspect of the train characteristics that cannot be seen in the field test. The engineering part is taken to the account in simulation. A set of training samples has been generated in the lab that will be discussed in the result discussion section. The number of rows is the number of cycles the application works that means the higher the number of the rows is better for training set. Also, the data set should include the full operation day to get a better picture of the revenue service in a long run operation.

Note that the delta speed for speed sensor is the difference of current cycle speed (current application cycle) and previous cycle speed (previous application cycle) for the same speed sensor. Basically, this delta speed is telling us how much the speed is changed (increase or decrease) from the previous cycle to the current cycle. Train speed is the average of speed sensor 1 and speed sensor 2. Train acceleration is the data from accelerometer that is used for data plausibility and witness in the model. The following steps should be taken for the core model in order to calculate the model's elements such as: extract pattern, pattern classification and plausibility:

2.3.2 PATTERN EXTRACTION STEP

This step is to extract the motion and traction patterns through the training data set. This step has to be run one and only one time. There are four sub-steps here to calculate prior probability, mean, variance and class conditional probability. The flow chart of the preliminary steps is given by Figure 2-2:

- Prior estimated probabilities of the states of the nature given by Equations 2-13, 2-14 and 2-15:

$$P(\omega_1) = \frac{\phi_{Slip}}{\phi_{Total}} \tag{2-13}$$

$$P(\omega_2) = \frac{\phi_{Normal}}{\phi_{Total}} \tag{2-14}$$

$$P(\omega_3) = \frac{\phi_{Slide}}{\phi_{Total}} \tag{2-15}$$

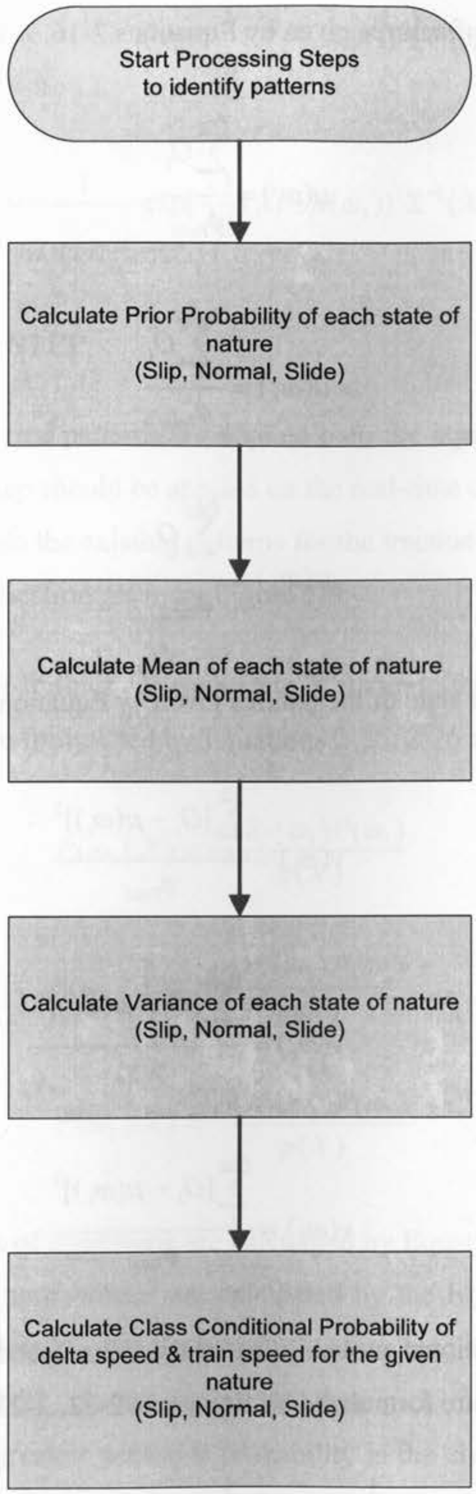

Figure 2-2: Bayesian Pattern Extraction

- Means of state of natures given by Equations 2-16, 2-17 and 2-18:

$$\mu(\omega_1) = \frac{\sum_{i}^{\phi_{Slip}} O_i}{\phi_{Total}} \tag{2-16}$$

$$\mu(\omega_2) = \frac{\sum_{i}^{\phi_{Normal}} O_i}{\phi_{Total}} \tag{2-17}$$

$$\mu(\omega_3) = \frac{\sum_{i}^{\phi_{Slide}} O_i}{\phi_{Total}} \tag{2-18}$$

- Variances of the state of the natures given by Equations 2-19, 2-20 and 2-21:

$$v(\omega_1) = \frac{\sum_{i}^{\phi_{Slip}} [O_i - \mu(\omega_1)]^2}{\phi_{Total}} \tag{2-19}$$

$$v(\omega_2) = \frac{\sum_{i}^{\phi_{Normal}} [O_i - \mu(\omega_2)]^2}{\phi_{Total}} \tag{2-20}$$

$$v(\omega_3) = \frac{\sum_{i}^{\phi_{Slide}} [O_i - \mu(\omega_3)]^2}{\phi_{Total}} \tag{2-21}$$

- The class conditional probabilities of the delta speed and train speed for the given state of natures are formulated by Equations 2-22, 2-23 and 2-24:

$$p(X \mid \omega_1) = \frac{1}{2\pi \mid \Sigma \mid^{\frac{1}{2}}} \exp[-\frac{1}{2}(X - \mu(\omega_1))' \Sigma^{-1} (X - \mu(\omega_1))] \tag{2-22}$$

$$p(X \mid \omega_2) = \frac{1}{2\pi |\Sigma|^{\frac{1}{2}}} \exp[-\frac{1}{2}(X - \mu(\omega_2))' \Sigma^{-1} (X - \mu(\omega_2))] \tag{2-23}$$

$$p(X \mid \omega_3) = \frac{1}{2\pi |\Sigma|^{\frac{1}{2}}} \exp[-\frac{1}{2}(X - \mu(\omega_3))' \Sigma^{-1} (X - \mu(\omega_3))] \tag{2-24}$$

2.3.3 CLASSIFICATION STEP

In this step, the extracted patterns are applied onto the input data to classify the traction conditions. The processing step should be applied on the real-time data input for each application cycle to classify the inputs into the existing patterns for the traction conditions. The flow chart of the processing steps in classification given by Figure 2-3:

- The posterior probabilities for each state of natures (tractions) for given delta speed and train speed are formulated by Equations 2-25, 2-26 and 2-27:

$$P(\omega_1 \mid X) = \frac{p(X \mid \omega_1) P(\omega_1)}{p(X)} \tag{2-25}$$

$$P(\omega_2 \mid X) = \frac{p(X \mid \omega_2) P(\omega_2)}{p(X)} \tag{2-26}$$

$$P(\omega_3 \mid X) = \frac{p(X \mid \omega_3) P(\omega_3)}{p(X)} \tag{2-27}$$

- Prior probabilities of conditions are calculated by Equations 2-13, 2-14 and 2-15. The class conditional probabilities are calculated by the Equations 2-22, 2-23 and 2-24. Evidence is calculated by the Equation 2-2. Upon receiving an input, apply Equations 2-25, 2-26 and 2-27, on the input data then pick the one with greater posterior probability. The greatest posterior probability is the classified traction for that input data. Repeat this process till the end for each application cycle. In case of the equal posterior probability or other issues like noise and lack of data in some application cycles, error and risk of classification need to be calculated. This part of the flow chart is considered as safety reaction for vital critical application. There is a counter to count the number of failures and if the number of failures exceeds the tolerance, it'll shut down the application to comply with safety critical fail-safe model.

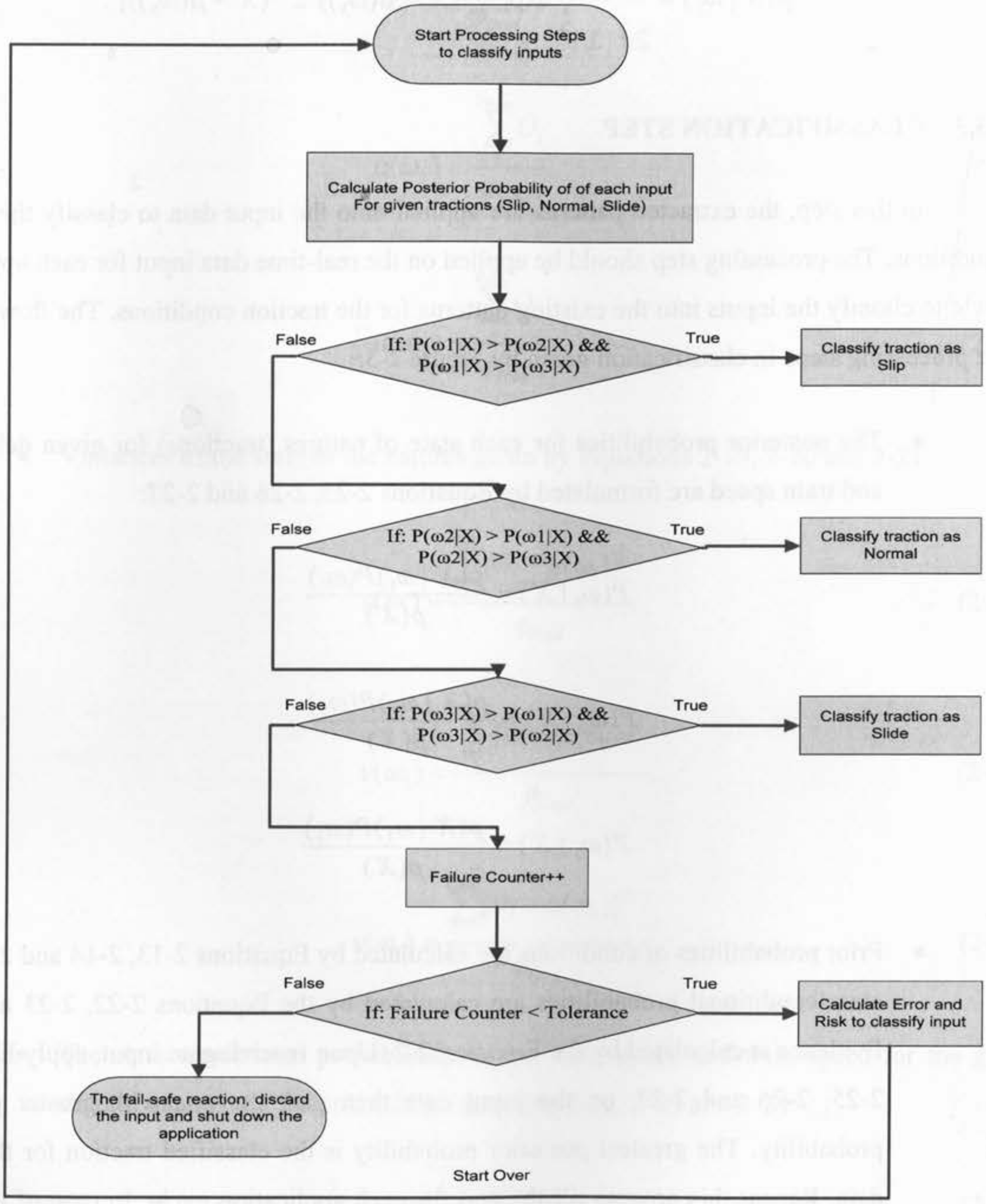

Figure 2-3: Bayesian Traction Classification

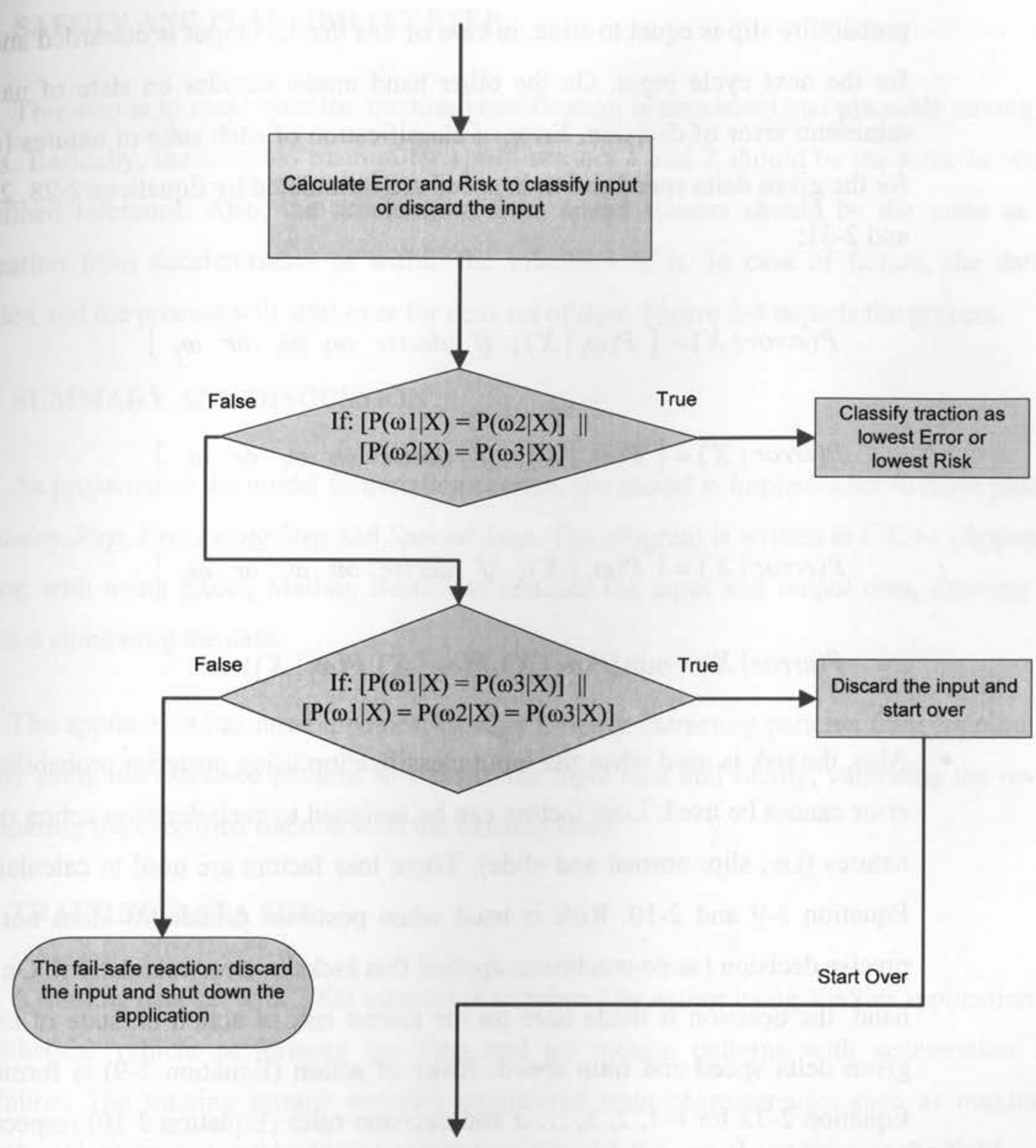

Figure 2-3: Bayesian Traction Classification (continue)

- The error classification is used when posterior probability does not give the certain classification (either posterior probability normal condition is equal to slip condition or posterior probability normal condition is equal to slide condition). Please note that, there is no possibility that either all posterior probabilities are equal or posterior probability slip is equal to slide, in case of this the data input is discarded and waiting for the next cycle input. On the other hand model decides on state of nature with minimum error of decision. Error of classification of each state of natures (tractions) for the given delta speed and train speed are formulated by Equations 2-28, 2-29, 2-30 and 2-31:

$$P(error \mid X) = \{\ P(\omega_1 \mid X);\ \ if\ \ \ decise\ \ on\ \ \omega_2\ \ or\ \ \omega_3\ \} \tag{2-28}$$

$$P(error \mid X) = \{\ P(\omega_2 \mid X);\ \ if\ \ \ decise\ \ on\ \ \omega_1\ \ or\ \ \omega_3\ \} \tag{2-29}$$

$$P(error \mid X) = \{\ P(\omega_3 \mid X);\ \ if\ \ \ decise\ \ on\ \ \omega_1\ \ or\ \ \omega_2\ \} \tag{2-30}$$

$$P(error \mid X) = \min\{P(\omega_1 \mid X), P(\omega_2 \mid X), P(\omega_3 \mid X)\} \tag{2-31}$$

- Also, the risk is used when the input classification using posterior probability and the error cannot be used. Loss factors can be assigned to each decision action on state of natures (i.e., slip, normal and slide). These loss factors are used to calculate risk by Equation 2-9 and 2-10. Risk is used when posterior probability does not give the precise decision (same conditions applied that kicks in error calculation). On the other hand, the decision is made base on the lowest risk of action on state of natures for given delta speed and train speed. Risks of action (Equation 2-9) is formulated by Equation 2-32 for *i*=1, 2, 3, … *a* and decision rules (Equation 2-10) respectively are formulated by Equations 2-32, 2-33, 2-34 and 2-35 for three states of natures:

$$R(\alpha_i \mid X) = [\lambda(\alpha_i \mid \omega_1)P(\omega_1 \mid X)] + [\lambda(\alpha_i \mid \omega_2)P(\omega_2 \mid X)] + [\lambda(\alpha_i \mid \omega_3)P(\omega_3 \mid X)] + \ldots \tag{2-32}$$

$$\text{Decide } \omega_1 : \text{if } R(\alpha_1 \mid X) = \min[R(\alpha_1 \mid X), R(\alpha_2 \mid X), R(\alpha_3 \mid X), \ldots] \tag{2-33}$$

$$\text{Decide } \omega_2 : \text{if } R(\alpha_2 \mid X) = \min[R(\alpha_1 \mid X), R(\alpha_2 \mid X), R(\alpha_3 \mid X), \ldots] \tag{2-34}$$

$$\text{Decide } \omega_3 : \text{if } R(\alpha_3 \mid X) = \min[R(\alpha_1 \mid X), R(\alpha_2 \mid X), R(\alpha_3 \mid X), \ldots] \tag{2-35}$$

2.3.4 SAFETY AND PLAUSIBILITY STEP

This step is to make sure the traction classification is consistent and plausible among the sensors. Basically, the detected traction for speed sensors 1 and 2 should be the same or within the defined tolerance. Also, the acceleration from speed sensors should be the same as the acceleration from accelerometer or within the tolerance of it. In case of failure, the data is discarded and the process will start over for next set of data. Figure 2-4 depicts the process.

2.4 SUMMARY AND DISCUSSION

As projected in the model formulation section, the model is implemented in three phases; *Preliminary Step*, *Processing Step* and *Special Step*. The program is written in C/C++ (Appendix B) along with using Excel, Matlab, BestFit to analyze the input and output data, drawing the charts and simulating the data.

The application has three modules, in which, firstly extracting patterns from training set, secondly using the extracted patterns to classify the input data and finally, validating the results by comparing the classified traction with the existing ones.

2.4.1 TRAINING DATA SET

A training data set with 2000 samples is simulated by author using VisSim application for a hypothetical vehicle performing the stop and go motion patterns with acceleration and deceleration. The training sample includes engineered train characteristics such as maximum acceleration/deceleration and braking curve to comply with the actual condition in the field.

Phase acceleration and phase deceleration are the key players in the traction because generally the spin happens in traction acceleration phase and the slide happens in the braking deceleration phase. The weather conditions (snow, rain) are contributing in traction condition, as such; the wheel adhesion to the rail is very depending on the dryness and wetness of the road. In the training samples the weather condition is ignored and has not been simulated.

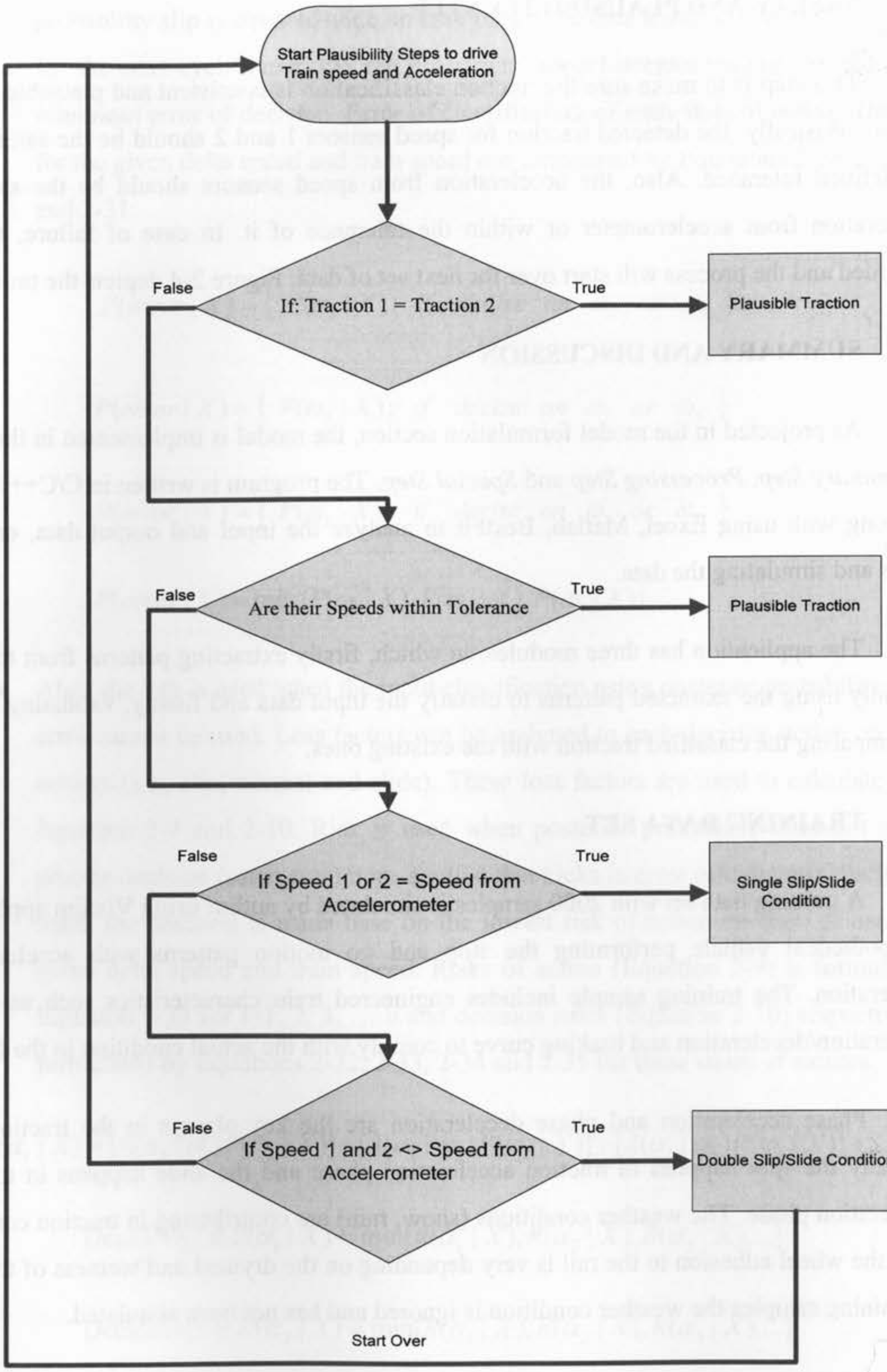

Figure 2-4: Bayesian Traction Plausibility

The training set has three columns of data that include speed sensor's signal (wheel speed, m/s), train speed (m/s) and traction conditions (slip=1, normal=2 and slide=3). The speed sensor's signal (wheel speed) is used to calculate the delta speed (x_1) and train speed (x_2) and possible tractions (ω_1=slip, ω_2=normal, ω_3=slide). For the input analysis the speed in the training set is analyzed by BestFit software to find out the probabilistic distribution and data integrity have been met for the model example. The result of distribution analysis, frequencies and data integrity of PP plot and QQ plot are shown by the Figures 2-5, 2-6, and 2-7.

Distribution charts (Figures 2-5) for data samples prove that the distribution is Gaussian using chi-square distribution for goodness of fit. However 5% P-value from each side of the region in Figure 2-5 showing that the probability of error in those area is 5% which is altogether 10%. Even though the P-value is 10% based on the chi-square test, but there is not much data (speed) distributed in those regions. For example there is no negative speed and there no speed more than 24.5 m/s due to the physical barrier of a train motion. Figures 2-6 and 2-7 both prove the integrity of the same samples. However, in figure 2-7 there is no straight line and the reason for that is half of the data is collected from different operation day. Note that the speed unit in this example is (m/s) and the acceleration unit is (m/s/s).

2.4.2 INPUT DATA SET

Input data set is collected from one of the field test (Appendix A) by the author with 200 records and three columns of data: speed sensor's signal (wheel speed), train speed and actual traction condition. Each record of data is considered as input for each application cycle (e.g., 100 ms) and implemented model runs through all records to classify the traction for each record (each row). Even though the traction condition is calculated by model, the measured traction condition in data sheet is for witness and validation purpose only.

2.4.3 RESULT DISCUSSION AND COMPARISON ANALYSIS

The output of the model is the traction classification along with plausibility check among the sensors (speed sensor 1, 2 and accelerometer). As a result of classification exercise and as a part of validation, the model's output is compared to the field test traction result (described in section 2.4.2) to validate the results. As a result of this comparison the traction classification is improved by 25% over the traditional results. 25% improvement is conducted from the counting of number of misclassifications in field test log vs. Bayesian classification. Which means Bayesian intelligent model shows better classification and more precise decision on noise and possible missing data along with low cost of error and risk of misclassification as per outlined in the model.

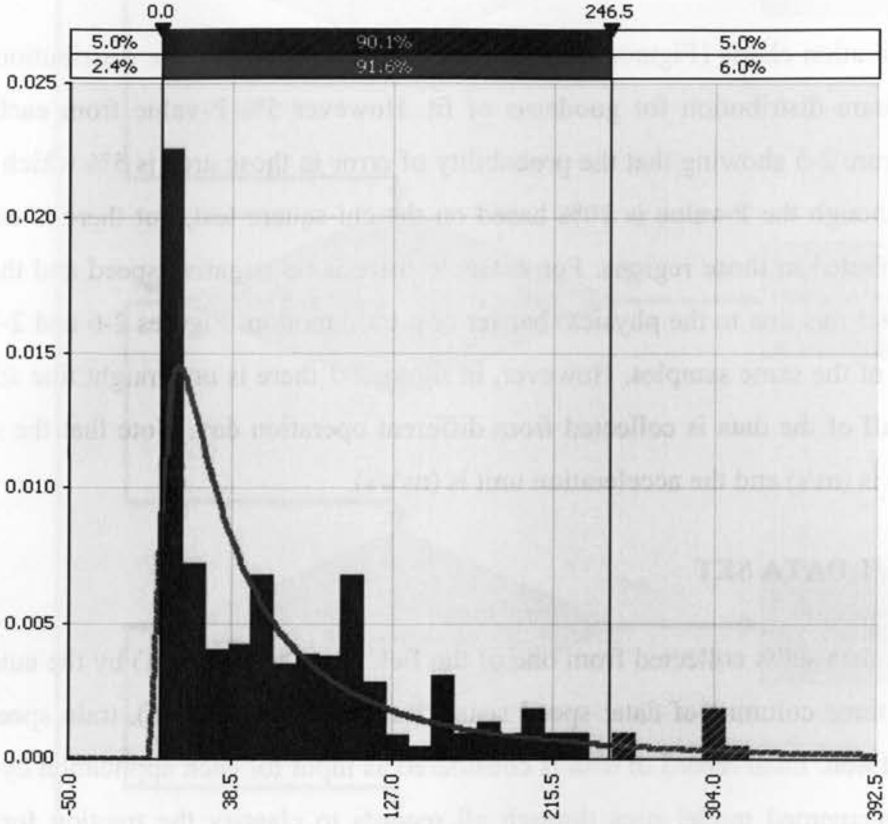

Figure 2-5: Training Samples Speed Distribution

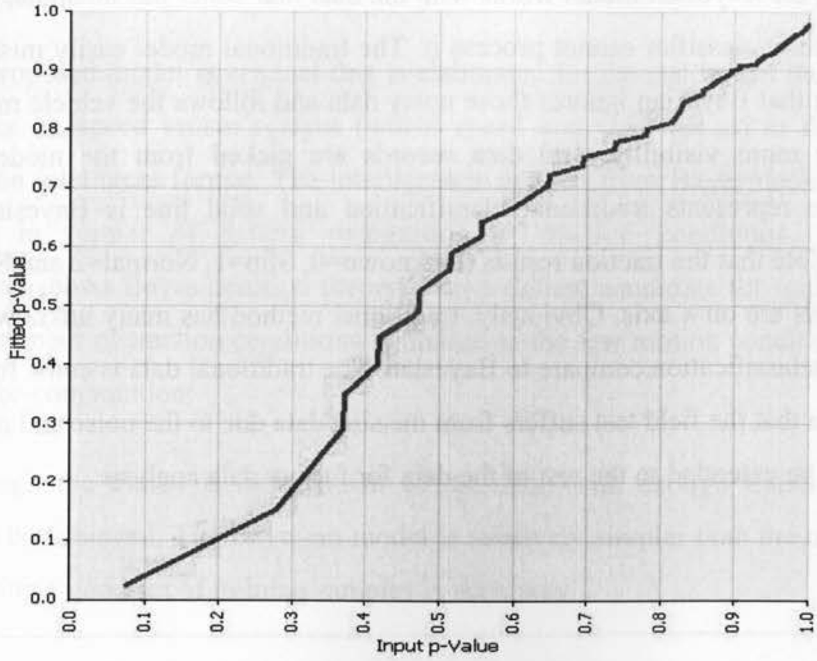

Figure 2-6: PP plot for Samples Data Integrity

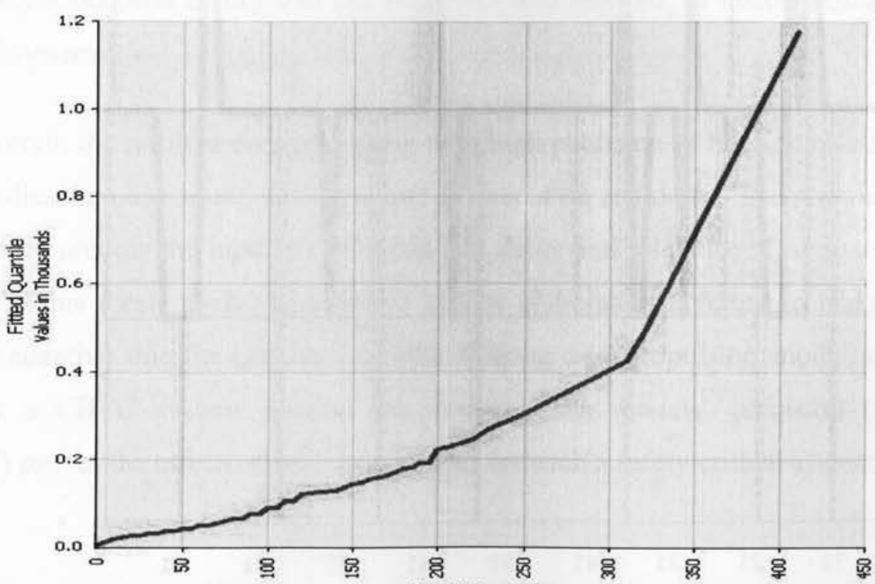

Figure 2-7: QQ plot for Samples Data Integrity

In fact, the Bayesian model works with the data that either has no signal or noise that the traditional traction classifier cannot process it. The traditional model easily mislead by noise or mistaken input that Bayesian ignores those noisy data and follows the vehicle motion pattern. In order to have more visibility, 100 data records are picked from the model's output. The perforated line represents traditional classification and solid line is Bayesian classification (Figure 2-8). Note that the traction results (Unknown=0, Slip=1, Normal=2 and Slide=3) are on y axis and records are on x axis. Obviously, traditional method has many unknown traction along with many misclassification compare to Bayesian. The traditional data is come from field test log and it is known that the field test suffers from missing data due to the noise and misclassification. This chart can be extended to the rest of the data for further data analysis.

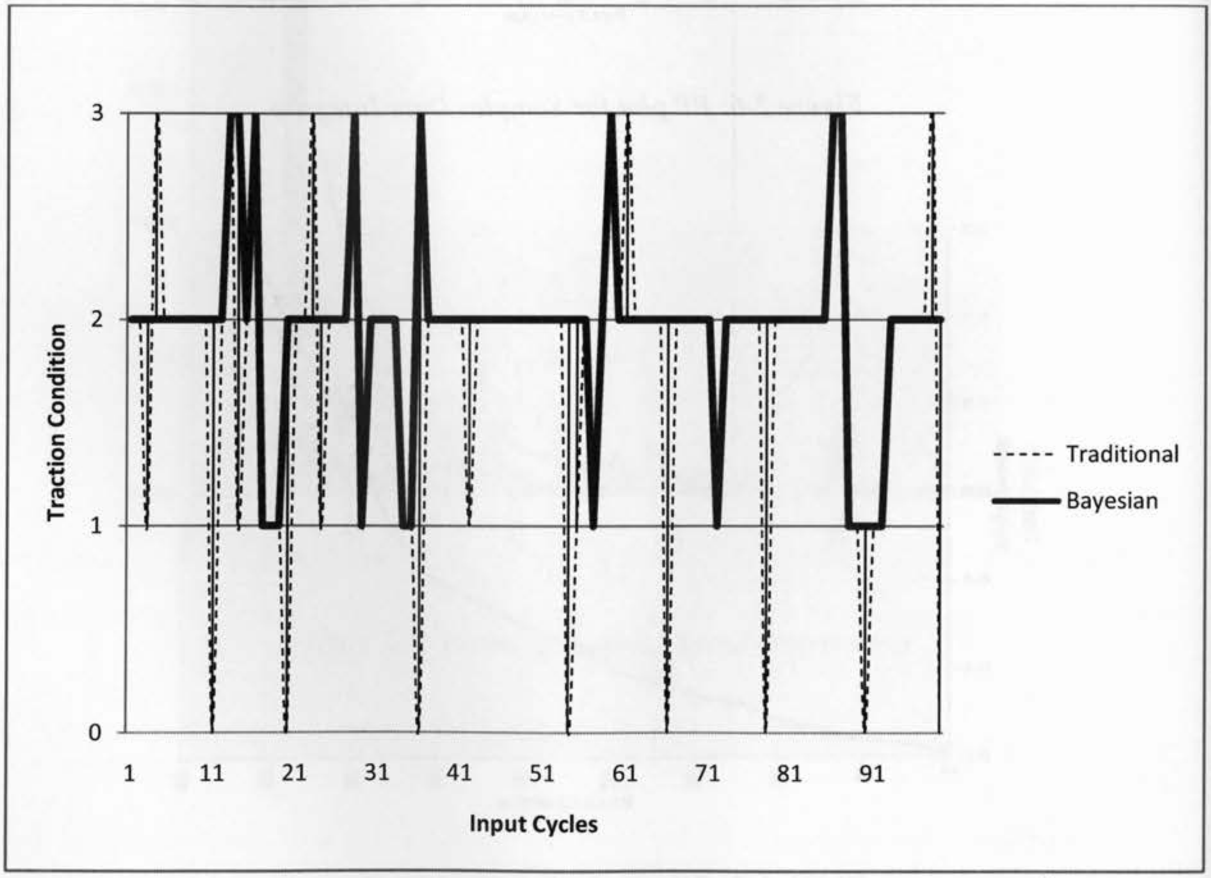

Figure 2-8: Traction Classification Comparison between Bayesian vs. Traditional

2.5 CONCLUSIONS

The proposed model is original that is elaborated for the rail transit industry. The safety model focuses on speed sensor's input (wheel speed and train speed) to detect the traction condition in an intelligent format. The intelligent is derived from Bayes decision theory that is implemented in format of pattern recognition of traction conditions. The practice of implementation shows Bayes decision theory is an excellent candidate for such a system due to fact that the number of traction conditions is limited to the few motion conditions which is very manageable for computation.

Although the model is independent of the data, with enough training sample higher precision can be achieved. The Bayesian model is relatively simpler than the traditional system; however, having a good set of training samples is necessary.

Training samples should include guideway condition, weather condition and vehicle characteristics. Vehicle engineering preparations are required to extract the patterns which are the key elements of the Bayesian model. Computer-based intelligent train traction safety model is using Bayes decision theory that has less error and less risk of misclassification compare to traditional systems.

Overall, the result is very promising with high precision of traction classification, and the model handles the noise along with low cost of execution and delay. The program is small and it is very fast to process the input and it needs less delay and tolerance. Traction mitigation is not discussed in this thesis study; however, it can be elaborated in future to make this intelligent model an adaptive one, in conjunction with braking and propulsion modules as they are all needed in a CBTC system. During the exercise, the models' precision (compare to the traditional) proves the effectiveness of the model for such a safety critical system.

CHAPTER 3: FUZZY TRACTION CONTROL SYSTEM

3.1 INTRODUCTION

A fuzzy Bayesian traction safety model is proposed for speed sensor vehicles in intelligent transportation systems. This model is also original and is formulated for such an integrated and complex system for ATO and ATP supervision. As mentioned in the introduction section and the Bayesian model section, the traction control system in this thesis is based on speed sensor data and can be integrated in complex systems such as CBTC or ATC under ATP and ATO supervisions. A similar configuration is followed in this section to have a better picture, especially if there is no much changed. Any sensors in control systems are subject to fail and noise. These signals sometimes may not be sensed, transmitted, or received precisely due to unexpected situations (i.e., sensor failure and noises), failure and noise bring uncertainty into the system. The uncertainty is started in the signal level and affects the management decision in the overall systematic picture.

Fuzzy theory is an excellent choice for such uncertain data inputs, (Zadeh, 1965). Therefore, the $\gamma-level$ fuzzy Bayesian model is proposed for sensor-based traction control system in this study. In order to apply the fuzzy Bayesian concept, the wheel acceleration (fuzzy signal) is assumed as fuzzy random variables with fuzzy prior distribution. The model's engine involves mathematical problem which can be solved in any programming language in on-board or embedded computers. Similar to the Bayesian section (section 2), the conceptual model is applied to a hypothetical case study with promising results for target and simulation systems.

Most of the fuzzy traction system applications are focusing on the motion of the wheel and rail terrain traction along the propulsion and braking system, (Sladover, 1991; Gillespie, 1992; Swaroop and Hedrick, 2001; and Khatun et al. 2001 and 2003). In rail transit systems, due to the limited motion dynamism and uncertainty of the sensors data, the fuzzy Bayesian model can be applied for the benefit of the safety and reliability to alleviate service interruptions during the revenue service. Some of new methods are already modeled in fuzzy logic but none of them are considered intelligent and they have not integrated in a complex system like a CBTC. Despite a lot of researches in traction control, the fuzzy applications are still complex and far from computation and has no knowledge of the vehicle characteristics, (Lee, 1990; Wang and Mendel, 1992; Wang, 1993; Constantin, 1996; Garcia-Riviera et al. 1997; Khatun et al. 1999; Cheok and Shiomi, 2000; Hiroaki et al. 2001; Frylmark and Johnsson, 2003).

This section aims at developing a fuzzy Bayesian traction detection safety model based on the Gaussian bell-shape distribution for the signals that sometimes may not be sensed, transmitted, or received precisely due to uncertain situations such as noise. It is assumed the fuzzy signals are fuzzy random variables with fuzzy prior distribution. Using the fuzzy signals, the dynamic risk of operation will be determined resulting in minimum cost and optimum service time. The focus of any sensor-based traction control is on speed sensors and accelerometer inputs to recognize and classify the traction condition. In order to recognize the traction conditions (i.e., normal and abnormal), the traction patterns need to be learned probabilistically.

The patterns can be formulated and classified under fuzzy set and fuzzy Bayesian decision theory, respectively, (Zadeh, 1965; Kandel, 1982; Bezdek and Sankar, 1992; Schnatter, 1992 and Duda et al. 2001). This decision theory is chosen due to firstly higher precision in processing the uncertain inputs, secondly the limited number of state of natures (traction conditions) and lastly manageable number of features (wheel acceleration), along with availability of prior knowledge of the traction conditions. Prior knowledge can be derived from field logs or can be simulated in lab along with knowing the vehicle's characteristics and engineering the track/vehicle behaviors. These behaviors such as guideway profile, max/min acceleration, max/min speed, weather condition and other mechanical aspects of the motion like tilt, banking, braking, weighting etc.

Fuzzy Bayesian decision theory is used to substantiate the intelligent management decision for such control system. The following sections are to show how the patterns are extracted from training samples using the Bayesian and fuzzy methods. The scope of the fuzzy method is to detect the signal level boundary for the normal condition and the abnormal condition. Similar to the previous section, data conversion, noise filtration, traction mitigation and motion adjustment are out of the scope of this study and assumed to be addressed by other modules in a CBTC system.

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Similar to the Bayesian the fuzzy model is generic and can be applied for any configuration of sensor, tachometer and accelerometer. For the configuring sensor, two speed sensors and one accelerometer are used to implement and study the model effectiveness. The accuracy of the model in fuzzy Bayesian decision theory depends on the distribution and membership function and having an ample number of samples for better result accuracy. Normally, any sample data is supposed to include all traction conditions for the project study. All patterns are supposed to be extracted prior to applying the model on the input data for classification. There are a few steps for the fuzzy Bayesian method including, initial step, processing step and special step.

As is well known, the fuzzy model works for the system with uncertain data input, along with knowing the patterns. The membership function is the most important part of the fuzzy Bayesian decision theory and should be analyzed prior to apply any further elaboration. As mentioned earlier, the input signal (wheel acceleration) is the fuzzy set for this model. Figure 3-1 demonstrates the process steps in the fuzzy Bayesian traction control system.

Basically, the input signal is used for fuzzification and is the transformation of the signal to understand format for the proposed model. Fuzzification is done for finding $\gamma-level$ fuzzy in random number format in the distribution graph as a result of Gaussian bell-shape distribution. γ can be given or can be derived from the random variable process using a fuzzy random function. In either case, by knowing γ , the border of the normal and abnormal is identified.

Most of the idea came from the transit system domain knowledge of the author along with extensive literature review of similar systems that have been modeled in the transportation industry. The proposed method is unique and is elaborated for the first time in the rail transit industry. Basically, the auto industry is leading in using fuzzy traction models, (Sladover, 1991; Jong and Chan, 1998; and Khatun et al. 2001), due to the dynamism of the market and economical competition. As mentioned earlier, the rail industry is slow to apply new techniques, due to the high cost of safety and reliability factors (Frylmark and Johnsson, 2003).

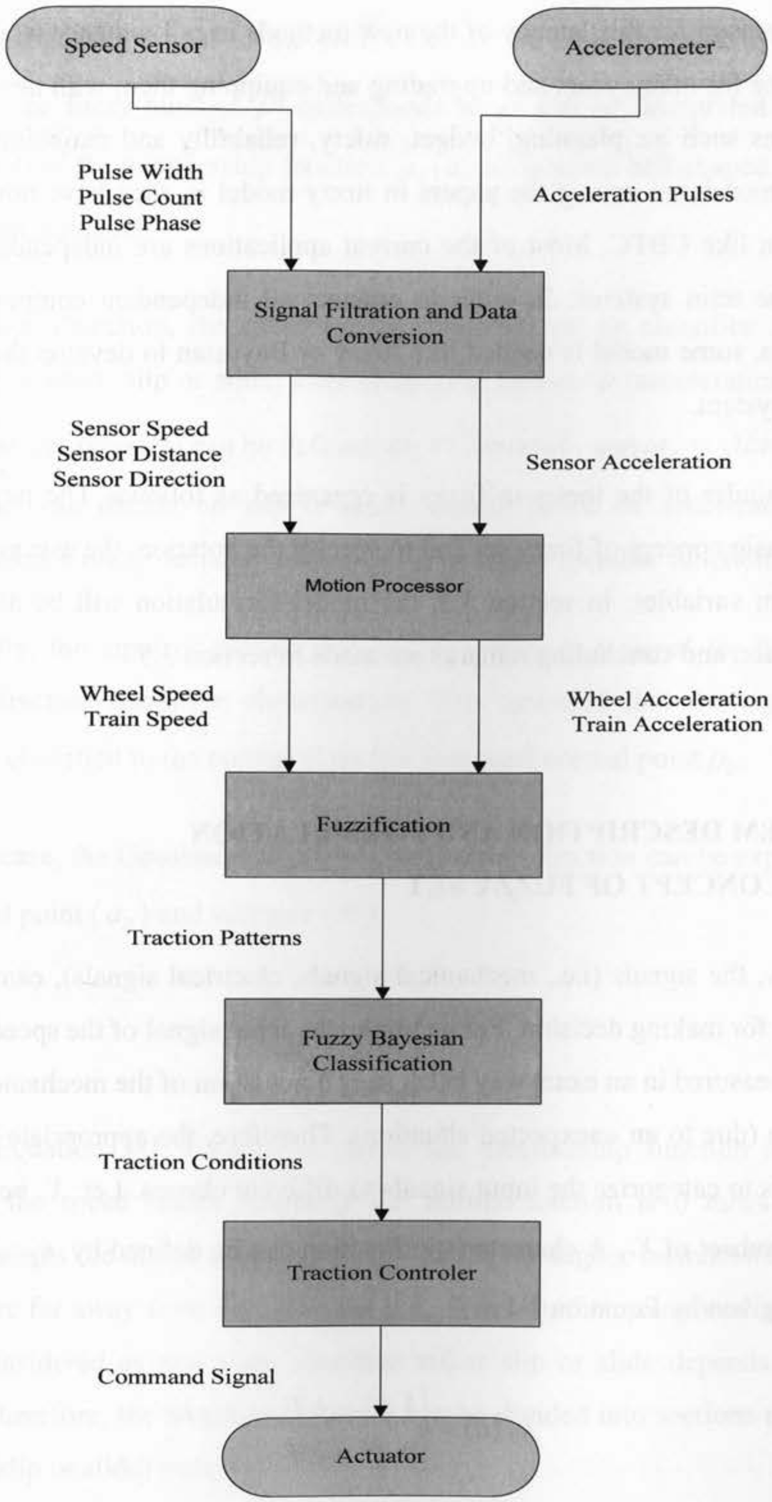

Figure 3-1: Fuzzy Intelligent Traction Control Steps

Another reason for this latency of the new methods in rail industry is, rail industry using vehicles in service for many years and upgrading and equipping them with new technology need a lot of attentions such as: planning, budget, safety, reliability and maintainability (Handoko, 2006). The common issue among the papers in fuzzy model is, they have not been part of any integrated system like CBTC. Most of the current applications are independent and work as a component in the train systems. In order to connect all independent components to make an integrated system, some model is needed like fuzzy or Bayesian to develop the channel through the supervision system.

The remainder of the thesis in fuzzy is organized as follows. The next section (3.2) is devoted to the basic concept of fuzzy set and to specify the notation, the assumptions concerning the fuzzy random variables. In section 3.3, the model formulation will be discussed. Also, an example illustration and concluding remarks are made in section 3.5.

3.2 PROBLEM DESCRIPTION AND FORMULATION

3.2.1 BASIC CONCEPT OF FUZZY SET

Generally, the signals (i.e., mechanical signals, electrical signals), cannot be considered as precise inputs for making decision. For example, the input signal of the speed sensor in a drive axel cannot be measured in an exact way because of fluctuation of the mechanical motion, sensor failure and noise (due to an unexpected situation). Therefore, the appropriate way to determine the signal level is to categorize the input signals to different classes. Let X be a universal fuzzy set and T be a subset of X. A characteristic function can be defined by $\kappa_T : X \longrightarrow \{0,1\}$ with respect to T as given by Equation 3-1:

$$\kappa_T(a) = \begin{cases} 1 \ if \ w \in T \\ 0 \ if \ w \notin T \end{cases} \qquad (3\text{-}1)$$

The concept of characteristic function can be extended to membership function $\mu_{\tilde{T}} : X \longrightarrow [0,1]$ for fuzzy subset $\tilde{T}$ of X. The value of $\mu_{\tilde{T}}(a)$ can be interpreted as the membership degree of a signal in the set $\widetilde{T}$. Let ρ be a signal received from speed sensor (acceleration). The fuzzy number $\widetilde{\rho}$ corresponds to ρ can be interpreted as "*around normal level*". The graph of the membership function $\mu_{\widetilde{T}}(a)$ is Gaussian bell-shaped and $\mu_{\widetilde{T}}(a) = 1$ when ρ is close to normal level.

In traction detection, the speed sensor signal should be classified to either normal or abnormal fuzzy classes (slip or slide) after measuring feature ρ (acceleration pulses). There are two states of natures (classes) can be defined: $\omega_1 = Normal$ and $\omega_2 = Abnormal$. In case of abnormal model can decide on slip or slide traction based on acceleration or deceleration condition. It makes a fuzzy decision on the area with higher member function result (likelihood).

Basically, the input of pattern recognition system is a signal for fuzzification and the output is the traction condition classification. It is assumed that the signal after Gaussian fuzzification is classified to the normal class if it is around normal point ρ_0.

In this case, the Gaussian bell-shape membership function can be expressed by Equation 3-2 with normal point (a_0) and variance (σ).

$$\mu_{\widetilde{T}}(a) = e^{\frac{-(a-a_0)^2}{2\sigma^2}} \tag{3-2}$$

Using Equation 3-2, Figure 3-2 shows the membership function for the acceleration received from the speed sensor assuming the normal traction is 0 m/s/s (meter per square second). This means the closer acceleration to 0 m/s/s, the higher membership function. Also, if accelerations are far away from normal point (i.e., 0 m/s/s), their membership function are close to zero and considered as abnormal condition either slip or slide depends on acceleration or deceleration. Therefore, the membership curve can be divided into sections representing normal and abnormal (slip or slide) tractions.

If $F(a)$ be the acceleration distribution function of a and $\mu_{\widetilde{T}}(a)$ be the traction membership function, the fuzzy probability of the class ω_j is given by Equation 3-3 for $\omega_1 = Normal$ and $\omega_2 = Abnormal$:

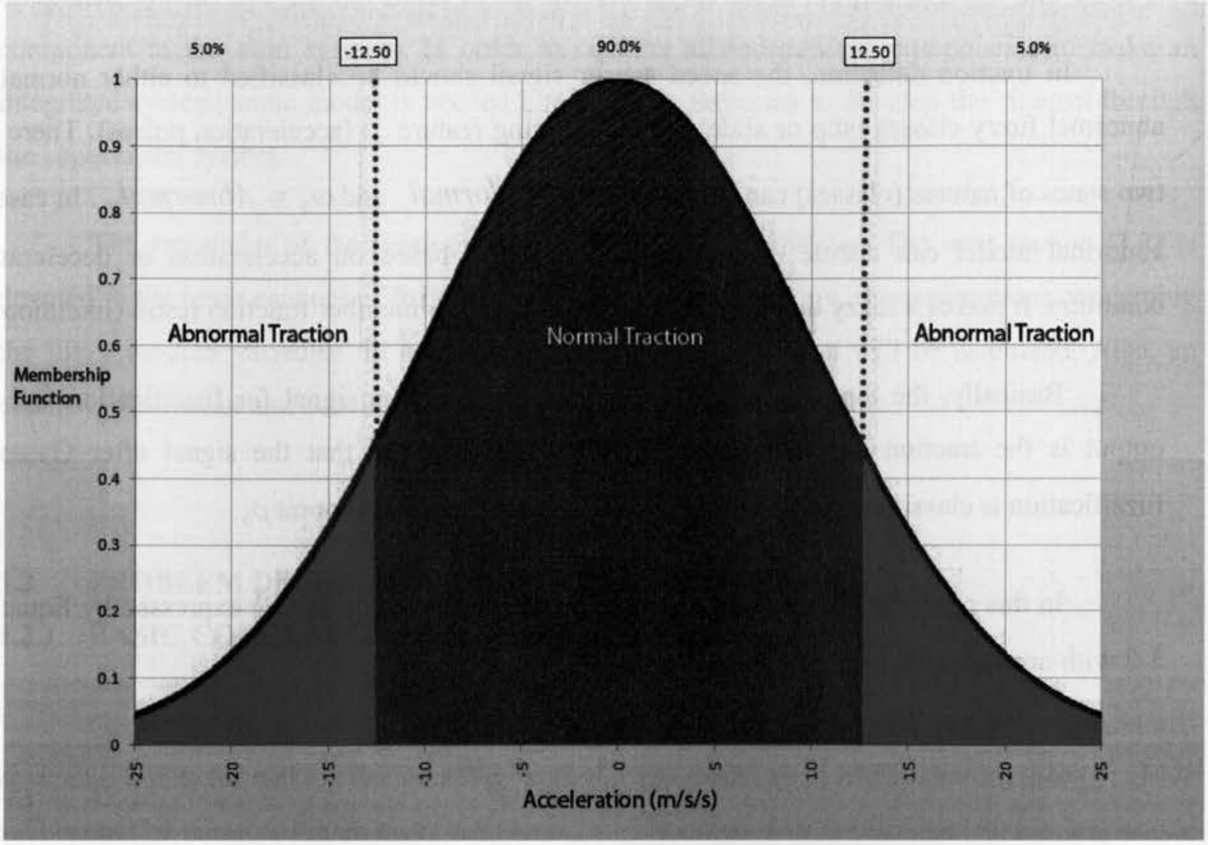

Figure 3-2: Gaussian Bell-Shape Membership Function for Wheel Acceleration Signals

$$\widetilde{P}(a \mid \omega_j) = \int_0^\infty \mu_{\widetilde{T}}(a).dF(a) \tag{3-3}$$

Similarly for fuzzy acceleration signals $\widetilde{\rho}_1, \widetilde{\rho}_2, ..., \widetilde{\rho}_n$ with corresponding membership functions $\mu_{\widetilde{T}}(a_1), \mu_{\widetilde{T}}(a_2), ..., \mu_{\widetilde{T}}(a_n)$, the fuzzy combined membership function can be formulated by Equations 3-4 and 3-5:

$$\mu_{\widetilde{T}}(\widetilde{\rho}_1, \widetilde{\rho}_2, ..., \widetilde{\rho}_n) = \min\{\mu_{\widetilde{T}}(a_1), \mu_{\widetilde{T}}(a_2), ..., \mu_{\widetilde{T}}(a_n)\} \tag{3-4}$$

$$\mu_{\widetilde{T}}(\widetilde{\rho}_1, \widetilde{\rho}_2, ..., \widetilde{\rho}_n) = \prod_{i=1}^{n} \mu_{\widetilde{T}_i}(a_i) \tag{3-5}$$

Although there are different rules to combine membership functions, (Schnatter, 1992), Equations 3-4 and 3-5 present suitable rules for classifying features and making decisions. The fuzzy random variable is needed to reflect monitoring notation of acceleration along with fuzzy parameters.

3.2.2 FUZZY RANDOM VARIABLES FOR INPUT SIGNALS

Let $\widetilde{\rho}$, is a speed sensor signal (acceleration), be a real number and $\widetilde{T}$ be a fuzzy subset of R. Normal class of (ω_j) can be denoted by $\widetilde{T}_\gamma(a) = \{a : \gamma \le \mu_{\widetilde{T}}(a) \le 1\}$ the $\gamma-level$set of $\widetilde{T}$ for $\gamma \in (0,1]$. Therefore Equation 3-3 can be formulated by Equation 3-6:

$$\widetilde{P}(a \mid \omega_j) = \int_{-\infty}^{\infty} \mu_{\widetilde{T}_\gamma}(a).dF(a) \tag{3-6}$$

$\widetilde{N}$ is fuzzy subset of R called a normal fuzzy set (ω_1) if there exists an $\widetilde{\rho}$ (acceleration signals) such that $\mu_{\widetilde{N}}(a) = 1$ for a given acceleration signal a. Similarly, $\widetilde{A}$ is fuzzy subset of R called an abnormal fuzzy set (ω_2) if there exists an $\widetilde{\rho}$ (acceleration signals) such that $(0 < \mu_{\widetilde{A}}(a) < \gamma)$ for all given acceleration signals a. In fact, for abnormal class the abnormal subset can be defined by $\widetilde{A}_\gamma(a) = \{a : \ \mu_{\widetilde{A}}(a) < \gamma\}$.

The pulse width signals can be transferred from the axels to the embedded system for traction control, which processes and interpreters the pulse signals into the known tractions (i.e., slip, normal and slide). The traction control system classifies the received signals to either 'Normal' or 'Abnormal' classes used for making traction decision. Abnormal can be interpret into slip or slide condition that depends on the motion condition.

There exist some sensor errors and unexpected situations that result in not having precise information from motion subsystem. As result, the fuzzy classifier that uses Bayesian Decision Theory is developed. Also, the membership function used in Bayesian Decision Theory is developed based on Gaussian Bell-shape membership described in Equation 3-2 for the traction condition associated with exponentially distributed pulse width acceleration signals.

3.2.3 FUZZY BAYESIAN DECISION RULES

As described in section 2, Bayesian decision theory is one method used to solve pattern recognition problems, when those problems are posed in a particular way along with prior knowledge. For classification, this is done by examining certain features of the objects and then classifying them as recognized item. This is exactly a pattern classification problem, (Duda et al. 2001). It makes a probabilistic decision on the area with higher likelihood. Bayes' formula can be expressed by posterior probability with knowing prior probability of the classes multiply by likelihood of the same class for given condition.

Basically, as formulated before, the Bayes formula is dealing with the posterior probability of a (ω_j) for given *feature* (x) using the prior probability of the same *class* (ω_j) and the class-conditional probability of *feature* (x) for given *class* (ω_j). Equation 2-1 gives the Bayes formulation, in which the evidence with *c* classes is formulated by Equation 2-2. In order to decide on the natures the Bayesian Decision Rules are used for two-category classes (c = 2) and any given *feature* (x) was given by Equation 2-5.

Similarly, the Bayesian decision rules can be extended for *c*-category classes for any given *feature* (x) is formulated by Equation 3-7, for $1 \le j \le c$:

$$\text{Decide}\, \omega_j \text{ ; if}\, P(\omega_j \mid x) = \max[\, P(\omega_1 \mid x), P(\omega_2 \mid x), \ldots, P(\omega_c \mid x)] \tag{3-7}$$

After determining the classes denoted by ω_j, the prior probabilities, $P(\omega_j)$, can be estimated based on training samples (historic data). Now, consider a fuzzy random variable, $\widetilde{\rho}$, with membership function, $\mu_{\widetilde{N}}(a)$ and the fuzzy subset $\widetilde{N}$ for Normal traction condition of wheel. The fuzzy Bayesian prior probabilities of classes (traction conditions) can be used for computing the fuzzy posterior probability as given by Equation 3-8:

$$\widetilde{P}(\omega_j \mid a) = \frac{\widetilde{p}(a \mid \omega_j) P(\omega_j)}{\widetilde{p}(x)} \tag{3-8}$$

Class conditional probability in Equation 3-8 can be replaced by Equation 3-6 to calculate fuzzy Bayesian posterior probability which is expressed by Equation 3-9, for all state of natures (classes):

$$\widetilde{P}(\omega_j \mid a) = \frac{P(\omega_j). \int_{-\infty}^{\infty} \mu_{\widetilde{T}_\gamma}(a).dF(a)}{\widetilde{p}(x)} \tag{3-9}$$

Applying Bayesian decision rules (Equation 2-5) over Equation 3-9 is giving us the fuzzy Bayesian decision rules that can be used to classify train tractions into the defined classes (i.e., normal and abnormal). Basically, Bayes gives us powerful decision making along with fuzzy theory that gives us pattern recognition capabilities along with finding the $\gamma - level$ of the membership function as the border of normal vs. abnormal condition.

3.3 MODEL FORMULATION

In order to apply the fuzzy Bayesian formulas, membership function, necessary features, state of natures (classes), probabilistic distribution, parameters and assumptions need to be introduced. All configuration and assumptions are discussed in the following sub-sections:

- Configuration: Two independent speed sensors are mounted on two independent train's axels with one accelerometer is mounted in the train. Also real-time application cycle is set to 100 ms therefore ($\lambda = 0.1$ s) for exponential distribution.
- Features: Delta speed (pulse width difference) is chosen as a feature which is equivalent to acceleration (a) as a result of speed change in a wheel sensor.

- State of Natures: There are two major state of nature as normal (ω_1) and abnormal (ω_2). In which abnormal is divided into slip or slide, depends on the acceleration or deceleration. At the end there will be three states of nature (classes) as slip/spin (ω_1), normal (ω_2) and slide (ω_3).
- Probabilistic Distribution: Gaussian bell-shaped distribution is selected for fuzzification of acceleration (pulse width signals) along with exponential probabilistic distribution of input samples with ($\lambda = 0.1$ s).
- Practical Approach: The fuzzy Bayesian rules are applied for each speed sensor and then compare against each other for plausibility purpose. To reach decision, the prior probability and class conditional probability for available state of natures (i.e., normal and abnormal) and features (i.e., delta speed or acceleration) are required. The patterns can be extracted from the training set into the intelligent format. The training data set should include three columns of data that two columns are for speed sensor 1, speed sensor 2 and the third column is for tractions. The third column is the real traction condition, which is derived from the lab simulation or field data collection.
- Application Cycle: Number of the rows is the number of cycles the application works, which means higher the number of the rows is better for training set. Also the data set should include the full operation day to get a better picture of the revenue service in a long run operation. Note that delta speed for speed sensor is the difference of current cycle speed (current application cycle) and previous cycle speed (previous application cycle) for the same speed sensor. Basically this delta speed is telling us, how much the wheel acceleration is for fuzzification. Train speed is the average of speed sensor 1 and speed sensor 2. Train acceleration is the data from accelerometer and is used for data plausibility and witness in the model.

The following sections should be taken for core model and in order to calculate the model's elements such as; membership function, extract patterns, pattern classification and plausibility:

3.3.1 PATTERN EXTRACTION STEP

This step is to extract the motion and traction patterns through the training data set. This step has to be run one and only one time. There are two sub-steps here to calculate prior probability and class conditional probability. The flow chart of the preliminary steps is given by Figure 3-3:

- Membership functions for fuzzy subsets of $\widetilde{N}$ (normal) and $\widetilde{A}$ (Abnormal) for $\gamma-level$ fuzzy Bayesian and given acceleration (a) are denoted by $\mu_{\widetilde{N}_\gamma}(a)$ and $\mu_{\widetilde{A}_\gamma}(a)$, respectively. Also distribution of input signals (acceleration) is assumed an exponential as given by Equation 3-10 with ($\lambda = 0.1$ s):

$$F(a) = \lambda e^{-\lambda a} \tag{3-10}$$

- Prior estimated probability of normal condition is given by Equation 3-11 and abnormal prior probability is given by Equation 3-12:

$$P(\omega_1) = \frac{\phi_{Normal}}{\phi_{Total}} \tag{3-11}$$

$$P(\omega_2) = \frac{\phi_{Slip} + \phi_{Slide}}{\phi_{Total}} \tag{3-12}$$

- Class conditional probabilities of acceleration (a) for given class (ω_1 =normal and ω_2 =abnormal) are given by Equation 3-13 and Equation 3-14, respectively:

$$\widetilde{p}(a \mid \omega_1) = \int_{\infty}^{\infty} \mu_{\widetilde{N}_\gamma}(a).dF(a) \tag{3-13}$$

$$\widetilde{p}(a \mid \omega_2) = \int_{-\infty}^{\infty} \mu_{\widetilde{A}_\gamma}(a).dF(a) \tag{3-14}$$

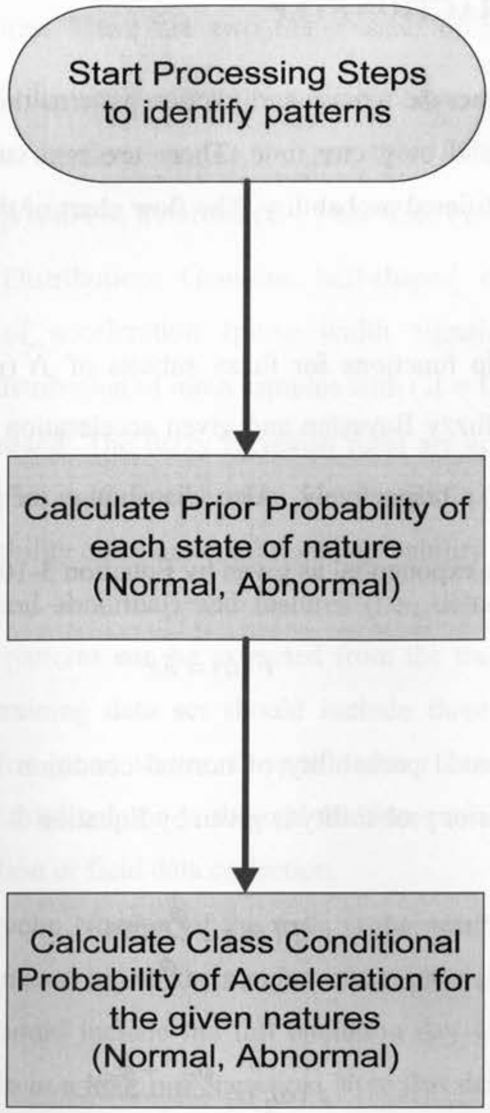

Figure 3-3: Fuzzy Pattern Extraction

3.3.2 CLASSIFICATION STEP

In this step, the extracted patters are applied onto the input data to classify the traction. The processing step should be applied on real-time data input in each application cycle to classify the inputs into the existing patterns for traction conditions. The flow chart of the classification steps is given by Figure 3-4:

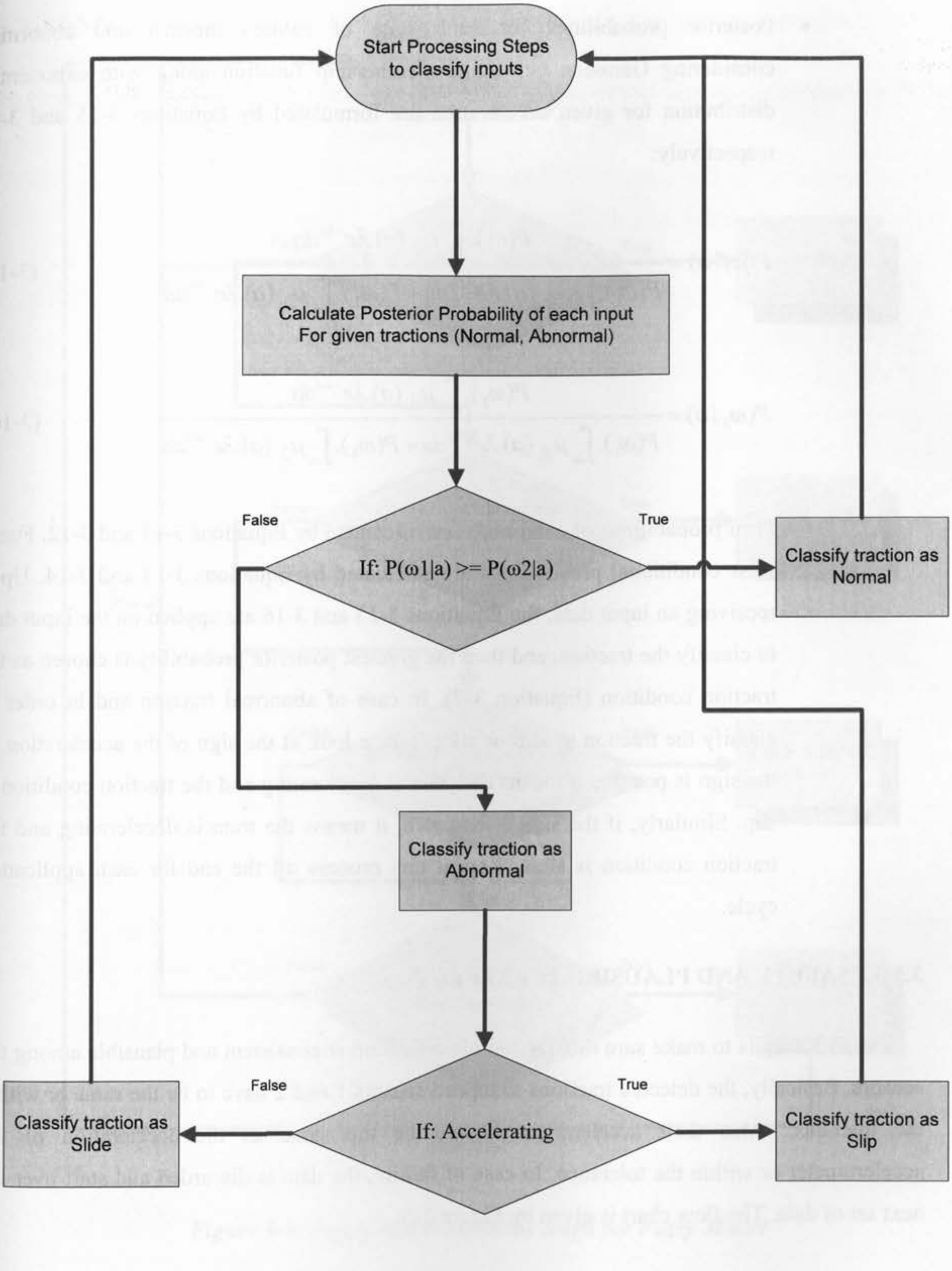

Figure 3-4: Fuzzy Traction Classification

- Posterior probabilities for each state of natures (normal and abnormal) considering Gaussian bell-shape membership function along with exponential distribution for given acceleration are formulated by Equations 3-15 and 3-16 respectively:

$$P(\omega_1 \mid a) = \frac{P(\omega_1).\int_{-\infty}^{\infty} \mu_{\tilde{N}_\gamma}(a).\lambda e^{-\lambda a} da}{P(\omega_1).\int_{-\infty}^{\infty} \mu_{\tilde{N}_\gamma}(a).\lambda e^{-\lambda a} da + P(\omega_2).\int_{-\infty}^{\infty} \mu_{\tilde{A}_\gamma}(a).\lambda e^{-\lambda a} da} \tag{3-15}$$

$$P(\omega_2 \mid a) = \frac{P(\omega_2).\int_{-\infty}^{\infty} \mu_{\tilde{A}_\gamma}(a).\lambda e^{-\lambda a} da}{P(\omega_1).\int_{-\infty}^{\infty} \mu_{\tilde{N}_\gamma}(a).\lambda e^{-\lambda a} da + P(\omega_2).\int_{-\infty}^{\infty} \mu_{\tilde{A}_\gamma}(a).\lambda e^{-\lambda a} da} \tag{3-16}$$

- Prior probabilities of conditions are calculated by Equations 3-11 and 3-12. Fuzzy class conditional probabilities are calculated by Equations 3-13 and 3-14. Upon receiving an input data, the Equations 3-15 and 3-16 are applied on the input data to classify the traction, and then the greatest posterior probability is chosen as the traction condition (Equation 3-7). In case of abnormal traction and in order to classify the traction as slip or slide, take a look at the sign of the acceleration. If the sign is positive it means the train is accelerating and the traction condition is slip. Similarly, if the sign is negative, it means the train is decelerating and the traction condition is slide. Repeat this process till the end for each application cycle.

3.3.3 SAFETY AND PLAUSIBILITY STEP

This step is to make sure the traction classification is consistent and plausible among the sensors. Basically, the detected tractions for speed sensors 1 and 2 have to be the same or within the tolerance. Also their accelerations should be the same as the acceleration of the accelerometer or within the tolerance. In case of failure, the data is discarded and start over for next set of data. The flow chart is given by Figure 3-5:

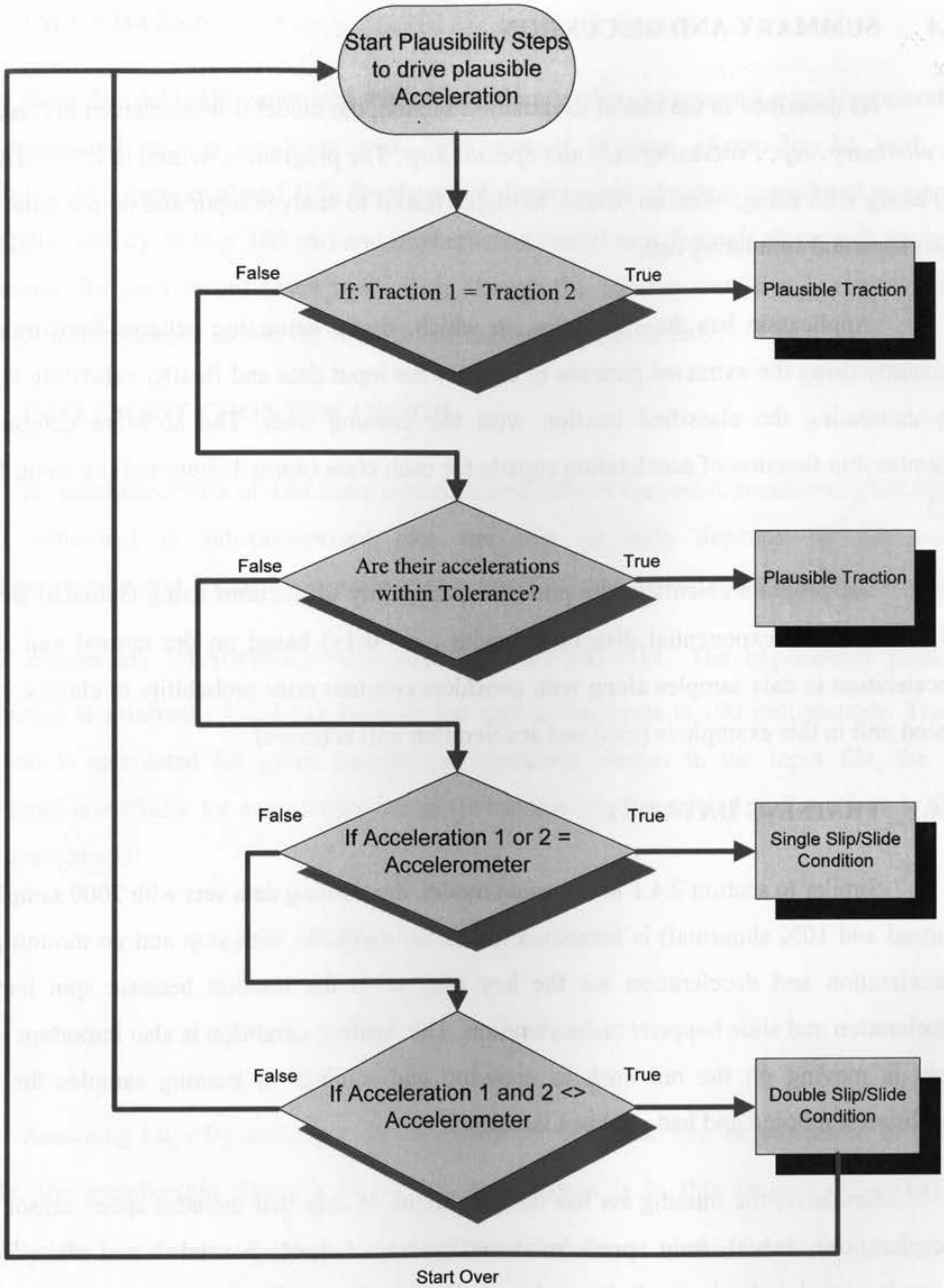

Figure 3-5: Safety and Plausibility Steps for Fuzzy Model

3.4 SUMMARY AND DISCUSSION

As described in the model formulation section, the model is implemented in three phases; *Preliminary Step*, *Processing Step* and *Special Step*. The program is written in C/C++ (Appendix C) along with using; WisSim, Excel, Matlab, BestFit to analyze input and output data, drawing the charts and simulating data.

Application has three modules, in which, firstly extracting patterns from training set, secondly using the extracted patterns to classify the input data and finally, validating the results by comparing the classified traction with the existing ones. The software determines the membership function of acceleration signals for each class (normal/abnormal) by using Equation 3-2

The program calculates the posterior probability of tractions using Gaussian Bell-Shape distribution and exponential distribution with ($\lambda = 0.1\,\text{s}$) based on the normal and abnormal acceleration in data samples along with considers constant prior probability of classes. Note that speed unit in this example is (m/s) and acceleration unit is (m/s/s).

3.4.1 TRAINING DATA SET

Similar to section 2.4.1 in Bayesian model, the training data sets with 2000 samples (90% normal and 10% abnormal) is simulated in lab for a vehicle with stop and go motion patterns. Acceleration and deceleration are the key players in the traction because spin happens in acceleration and slide happens in deceleration. The weather condition is also important when the train is moving on the rail such as snowing and raining. In training samples the weather condition is ignored and had not been simulated.

Similarly, the training set has three columns of data that includes speed sensor's signal (acceleration) (m/s/s), train speed (m/s) and traction (slip=1, normal=2 and slide=3). Speed sensor's signal (wheel speed) is used to calculate the acceleration along with knowing the existing tractions (ω_1=normal and ω_2=abnormal). In which the abnormal will be divided into slip or slide depends on the acceleration's sign. Note that the speed unit in this example is (m/s) and acceleration unit is (m/s/s).

3.4.2 INPUT DATA SET

Input data set is also simulated with three columns of speed sensor's signal (acceleration), train speed and traction condition with 2000 records of data, (Appendix A), with prior probability 90% for normal and 10% for abnormal. Each record of data is considered as input for each application cycle (e.g. 100 ms) and implemented model runs through all records to classify the traction for each record (each row). Even though the traction condition is calculated, the existing traction in input data is for witness and validation purpose only.

3.4.3 IMPLEMENTATION DISCUSSION

As mentioned 90% of data input is normal and 10% of the rest is considered abnormal. In which, abnormal is sub-categorized into the slip or slide depends on the traction (acceleration=slip and deceleration=slide). As a result of model exercise, the prior probabilities of the classes are $P(Normal) = 0.9$ and $P(Abnormal) = 0.1$. The exponential parameter distribution is assumed ($\lambda = 0.1\,\text{s}$), because the application cycle is 100 milliseconds. Traction condition is calculated for given normal and abnormal classes in the input file, the class conditional probability for acceleration for given traction are formulated as Equations 3-17 and 3-18, respectively:

$$\tilde{p}(a \mid Normal) = \mu_{\tilde{N}_\gamma}(a)\lambda e^{-\lambda a} \tag{3-17}$$

$$\tilde{p}(a \mid Abnormal) = \mu_{\tilde{A}_\gamma}(a)\lambda e^{-\lambda a} \tag{3-18}$$

Assuming ($a_0 = 0$) and ($\sigma = 10$), for given $\gamma - level$ that can be calculated in training sample, the membership function of normal acceleration is in this range ($\gamma \le \mu_{\tilde{N}_\gamma}(a) \le 1$). Similarly, the membership function of abnormal acceleration is in this range ($0 < \mu_{\tilde{A}_\gamma}(a) < 1$). Finally, the posterior probability of fuzzy Bayesian for decision making of all acceleration inputs for given traction (normal/abnormal) are denoted by Equation 3-19 and Equation 3-20:

$$P(Normal \mid a) = \frac{P(Normal).\mu_{\tilde{N}_\gamma}(a)\lambda e^{-\lambda a}}{P(Normal).\mu_{\tilde{N}_\gamma}(a)\lambda e^{-\lambda a} + P(Abnormal).\mu_{\tilde{A}_\gamma}(a)\lambda e^{-\lambda a}} \tag{3-19}$$

$$P(Abnormal \mid a) = \frac{P(Abnormal).\mu_{\tilde{A}_\gamma}(a)\lambda e^{-\lambda a}}{P(Normal).\mu_{\tilde{N}_\gamma}(a)\lambda e^{-\lambda a} + P(Abnormal).\mu_{\tilde{A}_\gamma}(a)\lambda e^{-\lambda a}} \tag{3-20}$$

3.4.4 RESULTS DISCUSSION AND COMPARISON ANALYSIS

The classification of data input is given by Equations 3-19 and 3-20 that program runs through all inputs to classify the traction conditions. Similar to Bayesian model the output of the model is the traction classification along with plausibility check among the sensors (speed sensor 1, 2 and accelerometer).

The model's output is compared to the Bayesian traction (result discussion in section 2.4.3) to validate the results. As a result of this comparison the traction classification is improved by 5% over the Bayesian results, which means the fuzzy model has a bit improved compare to the Bayesian in the decision and classification criteria. There is no much execution cost different between Bayesian and fuzzy that both are considered with low error and risk of misclassification as per outlined in the model.

Basically, the fuzzy model works with the uncertain data especially the noisy acceleration. Unlike traditional model that easily mislead by noise or misclassification traction, the fuzzy model absorbs all uncertain oscillation under the train behavior.

As a result of implementation exercise, if a membership function of an acceleration is higher than $\gamma = 0.25$ for (-16.45 m/s/s/< acceleration < 16.45 m/s/s), it is considered as normal traction and below the $\gamma = 0.25$ (acceleration <= -16.45 m/s/s and acceleration >= 16.45 m/s/s) is considered abnormal traction that cause slip or slide. Assuming the normal acceleration, ρ_0, with γ =0.25 as level normal level.

Figure 3-6 depicts the bell-shape distribution of membership function of tractions (normal and abnormal) in data input.

In order to have more visibility 100 data records are picked from the model's output (Figure 3-7). Solid line represents Bayesian classification and perforated line is Bayesian classification. As visible there is some misclassification in Bayesian vs. fuzzy. Note that the traction results (Unknown=0, Slip=1, Normal=2 and Slide=3) are on y axis and records are on x axis.

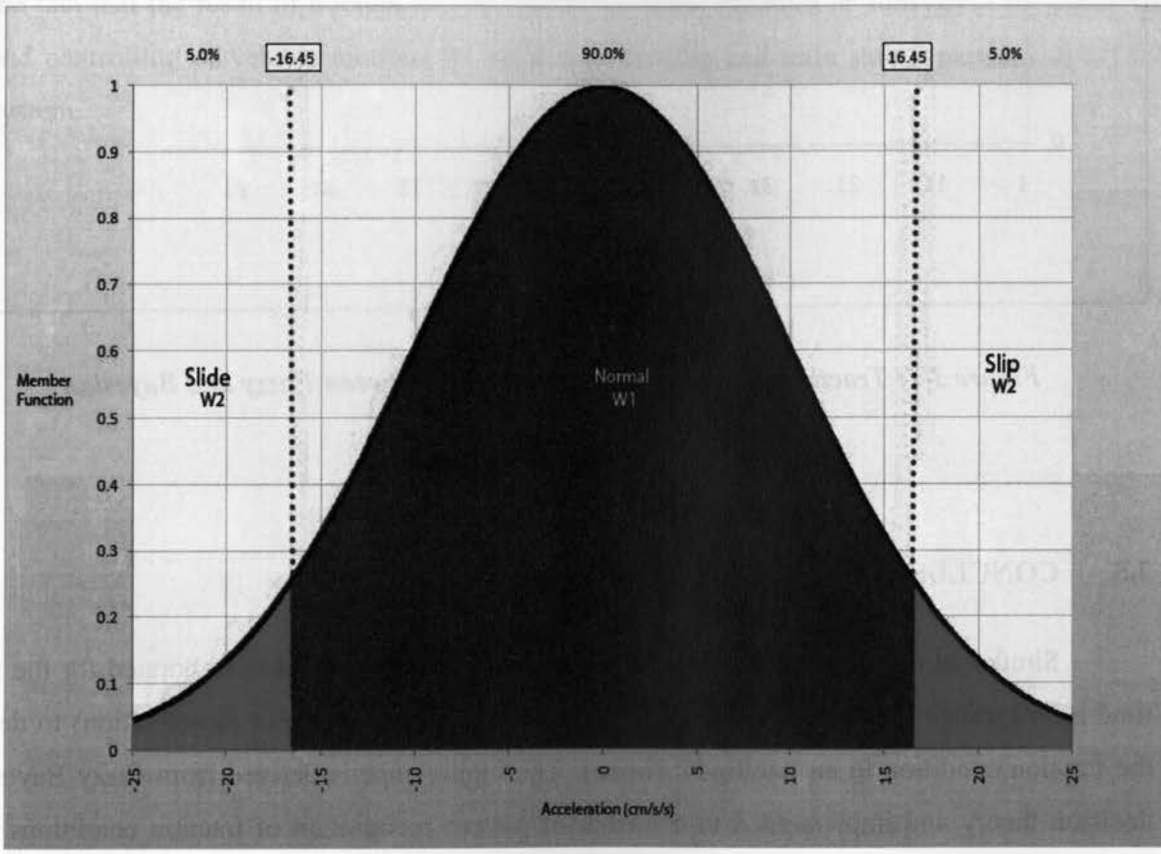

Figure 3-6: Gaussian Bell-Shape Fuzzy Membership Function for Data Input

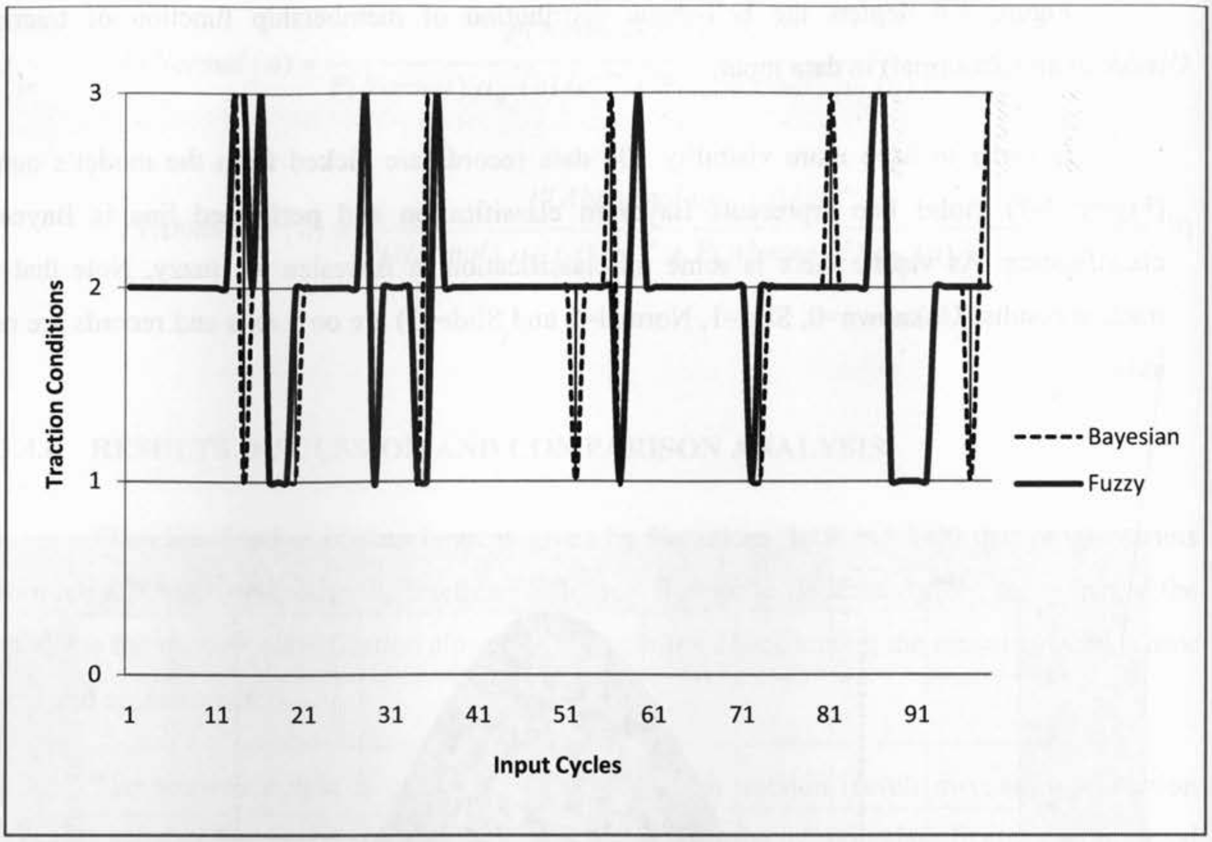

Figure 3-7: Traction Classification Comparison between Fuzzy and Bayesian

3.5 CONCLUSIONS

Similar to the Bayesian model, the fuzzy model is unique and is elaborated for the first time in rail transit industry. The model focuses on speed sensor's input (acceleration) to detect the traction condition in an intelligent format. The intelligence is derived from fuzzy Bayesian decision theory and implemented in a format of pattern recognition of traction conditions and $\gamma - level$ fuzzy. The implementation exercise shows the effectiveness of the model that is a good choice for such an integrated and complex system. Applying the fuzzy Bayesian decision rules is easy and takes less fine tuning and field engineering time in any projects.

Similar to the Bayesian model, an ample number of training samples can help to extract all aspects of the vehicle behaviors. The fuzzy Bayesian model is very precise with low error cost. Overall, the result is very promising with high precision and low cost. The analysis shows the Bayesian and fuzzy models are very similar in terms of implementation and cost of engineering. Both models need training samples and they need to extract vehicle patterns. Basically the difference is, the Bayesian model focuses on the wheel speed and train speed as features and the fuzzy model focuses on the wheel acceleration as feature.

The application of these two methods depends on the system and vehicle engineering and wayside configuration. Both methods are very good candidates for an integrated system due to the fact that the result of traction can be sent to the other modules or subsystem for supervision and controlling of vehicle motions for train safe barking and train safe separation in a CBTC system.

CHAPTER 4: CONCLUSIONS AND FUTURE WORK

4.1 CONCLUSIONS

In this thesis, two techniques were proposed as the "Bayesian model" and the "fuzzy model". Intelligent techniques were identified to be the most capable techniques for traction control in computer-based transit control systems due to the precision in traction classification. As discussed in the conclusion sections of Bayesian model (chapter 2) and the fuzzy model (chapter 3), both models have been implemented successfully, along with a full description of data analysis. Overall, both methods are very effective in technical aspects and in low cost of engineering. These two methods are highly recommended for an application of traction control in any CBTC along with ATO and ATP supervisions, to operate precisely with a low cost of maintenance and with a high level of reliability and safety standards. Choosing between the Bayesian and fuzzy models depends on the engineering application and configuration. The Bayesian model focuses on the speed and its pattern and the fuzzy model focuses on acceleration as input signal. The following items are considered the strong points of an intelligent model, whether Bayesian or fuzzy:

- Vehicle characterization are included in model,
- Vehicle characteristics' patters play the key role in train traction,
- Training samples can be collected from the field including vehicle characteristics,
- Training samples can be generated in lab including vehicle characteristics,
- Intelligent model is simple to implement, and easy to validate,
- Intelligent model is generic with promising results,
- Intelligent model is compatible with existing sensor configuration,
- Intelligent model is in very high accuracy and high precision,
- Noise is absorbed in vehicle characteristics and patterns,
- Tolerance and persistency are very low and easy to handle, and

Model is very flexible to any type of new sensors.

The thesis objectives regarding to precision and classification were met for both models, according to the results analysis, and both models can overcome the challenges that are faced in the ATC traction control system.

4.2 FUTURE WORK

Overall, the proposed models are satisfy the objectives of the thesis and are ample for showing the effectiveness of the models; however, there are some potential improvements suggested as a result of this thesis as follows:

- Extending the Bayesian model to include at least three features (i.e., delta speed, speed and acceleration) for better pattern recognition.
- Extending the fuzzy model to include at least two input signals (i.e., speed sensor, accelerometer or adhesion factor) for better fuzzification of the vector signal.
- Training samples should include more data, including weather conditions, guideway characteristics, grades and speed profile to include all possible patterns.
- Stress test the model by running field test and with higher speed traction.

APPENDIX A

Partial presentation of input data (500 records):

Input Data			
Application Cycle 100 ms	W1=Slip=1	W2=Normal=2	W3=Slide=3
Speed Sensor (m/s)	Measured Acceleration (m/s/s)	Measured Traction Conditions	Membership Function
0.00	0.00	2	1.00
1.00	10.00	2	1.00
2.00	10.00	2	0.98
3.50	15.00	2	0.94
4.00	5.00	2	0.92
5.00	10.00	2	0.88
6.50	15.00	2	0.81
7.00	5.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67
10.00	10.00	2	0.61
11.50	15.00	2	0.52
15.00	35.00	3	0.32
16.65	16.45	3	0.25
18.00	13.55	2	0.20
25.00	70.00	3	0.04
20.00	-50.00	1	0.14
15.50	-45.00	1	0.30
12.00	-35.00	1	0.49
13.00	10.00	2	0.43
14.00	10.00	2	0.38
15.00	10.00	2	0.32
16.00	10.00	2	0.28
17.00	10.00	2	0.24
18.50	15.00	2	0.18
19.00	5.00	2	0.16
20.00	10.00	2	0.14
22.00	20.00	3	0.09
19.00	-30.00	1	0.16
18.00	-10.00	2	0.20
17.00	-10.00	2	0.24

16.00	-10.00	2	0.28
15.00	-10.00	2	0.32
8.00	-70.00	1	0.73
1.00	-70.00	1	1.00
12.00	110.00	3	0.49
11.00	-10.00	2	0.55
10.50	-5.00	2	0.58
9.00	-15.00	2	0.67
8.00	-10.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.00	-10.00	2	0.92
3.00	-10.00	2	0.96
2.00	-10.00	2	0.98
1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
4.50	45.00	3	0.90
3.00	-15.00	2	0.96
2.00	-10.00	2	0.98
1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00

1.00	10.00	2	1.00
2.50	15.00	2	0.97
3.00	5.00	2	0.96
4.00	10.00	2	0.92
5.00	10.00	2	0.88
6.00	10.00	2	0.84
7.00	10.00	2	0.78
8.50	15.00	2	0.70
9.00	5.00	2	0.67
10.00	10.00	2	0.61
11.00	10.00	2	0.55
31.00	200.00	3	0.01
41.00	100.00	3	0.00
31.00	-100.00	1	0.01
25.00	-60.00	1	0.04
20.50	-45.00	1	0.12
15.00	-55.00	1	0.32
12.00	-30.00	1	0.49
12.00	0.00	2	0.49
11.00	-10.00	2	0.55
10.00	-10.00	2	0.61
9.00	-10.00	2	0.67
8.00	-10.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.00	-10.00	2	0.92
3.50	-5.00	2	0.94
2.00	-15.00	2	0.98
1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00
1.00	10.00	2	1.00

2.50	15.00	2	0.97
3.00	5.00	2	0.96
4.00	10.00	2	0.92
5.00	10.00	2	0.88
6.00	10.00	2	0.84
7.00	10.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67
10.00	10.00	2	0.61
11.00	10.00	2	0.55
12.00	10.00	2	0.49
11.00	-10.00	2	0.55
10.50	-5.00	2	0.58
9.00	-15.00	2	0.67
8.00	-10.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.00	-10.00	2	0.92
3.50	-5.00	2	0.94
2.00	-15.00	2	0.98
1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.50	15.00	2	0.97
2.00	-5.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00
1.00	10.00	2	1.00
2.00	10.00	2	0.98
3.00	10.00	2	0.96
4.00	10.00	2	0.92
5.00	10.00	2	0.88
6.00	10.00	2	0.84
7.00	10.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67

10.00	10.00	2	0.61
11.00	10.00	2	0.55
23.00	120.00	3	0.07
32.00	90.00	3	0.01
22.00	-100.00	1	0.09
23.00	10.00	2	0.07
20.00	-30.00	1	0.14
18.00	-20.00	1	0.20
12.00	-60.00	1	0.49
4.00	-80.00	1	0.92
9.50	55.00	3	0.64
15.00	55.00	3	0.32
13.00	-20.00	1	0.43
11.00	-20.00	1	0.55
10.00	-10.00	2	0.61
9.00	-10.00	2	0.67
8.00	-10.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.50	-5.00	2	0.90
3.00	-15.00	2	0.96
2.00	-10.00	2	0.98
1.00	-10.00	2	1.00
0.00	-10.00	2	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00
1.00	10.00	2	1.00
2.00	10.00	2	0.98
3.50	15.00	2	0.94
4.00	5.00	2	0.92
5.00	10.00	2	0.88
6.00	10.00	2	0.84
7.00	10.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67
10.00	10.00	2	0.61
11.00	10.00	2	0.55
31.00	200.00	3	0.01
41.00	100.00	3	0.00
31.00	-100.00	1	0.01
25.00	-60.00	1	0.04
20.00	-50.00	1	0.14

15.00	-50.00	1	0.32
12.00	-30.00	1	0.49
13.00	10.00	2	0.43
14.00	10.00	2	0.38
15.50	15.00	2	0.30
16.00	5.00	2	0.28
17.00	10.00	2	0.24
18.00	10.00	2	0.20
19.00	10.00	2	0.16
20.00	10.00	2	0.14
22.00	20.00	3	0.09
19.00	-30.00	1	0.16
18.00	-10.00	2	0.20
17.00	-10.00	2	0.24
16.00	-10.00	2	0.28
15.00	-10.00	2	0.32
8.00	-70.00	1	0.73
1.00	-70.00	1	1.00
12.00	110.00	3	0.49
11.50	-5.00	2	0.52
10.00	-15.00	2	0.61
9.00	-10.00	2	0.67
8.00	-10.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.00	-10.00	2	0.92
3.00	-10.00	2	0.96
2.00	-10.00	2	0.98
1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
4.00	40.00	3	0.92
3.50	-5.00	2	0.94

2.00	-15.00	2	0.98
1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00
1.00	10.00	2	1.00
2.50	15.00	2	0.97
3.00	5.00	2	0.96
4.00	10.00	2	0.92
5.00	10.00	2	0.88
6.00	10.00	2	0.84
7.00	10.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67
10.00	10.00	2	0.61
11.00	10.00	2	0.55
31.00	200.00	3	0.01
41.00	100.00	3	0.00
31.00	-100.00	1	0.01
25.00	-60.00	1	0.04
20.00	-50.00	1	0.14
15.50	-45.00	1	0.30
12.00	-35.00	1	0.49
12.00	0.00	2	0.49
11.00	-10.00	2	0.55
10.00	-10.00	2	0.61
9.00	-10.00	2	0.67
8.00	-10.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.00	-10.00	2	0.92
3.50	-5.00	2	0.94
2.00	-15.00	2	0.98

1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00
1.00	10.00	2	1.00
2.00	10.00	2	0.98
3.00	10.00	2	0.96
4.00	10.00	2	0.92
5.00	10.00	2	0.88
6.00	10.00	2	0.84
7.00	10.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67
10.00	10.00	2	0.61
11.50	15.00	2	0.52
12.00	5.00	2	0.49
11.00	-10.00	2	0.55
10.00	-10.00	2	0.61
9.00	-10.00	2	0.67
8.00	-10.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.00	-10.00	2	0.92
3.50	-5.00	2	0.94
2.00	-15.00	2	0.98
1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00

2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00
1.00	10.00	2	1.00
2.00	10.00	2	0.98
3.00	10.00	2	0.96
4.00	10.00	2	0.92
5.50	15.00	2	0.86
6.00	5.00	2	0.84
7.00	10.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67
10.50	15.00	2	0.58
11.00	5.00	2	0.55
23.00	120.00	3	0.07
32.00	90.00	3	0.01
22.00	-100.00	1	0.09
23.00	10.00	2	0.07
20.00	-30.00	1	0.14
18.00	-20.00	1	0.20
12.00	-60.00	1	0.49
4.00	-80.00	1	0.92
9.00	50.00	3	0.67
15.00	60.00	3	0.32
13.00	-20.00	1	0.43
11.50	-15.00	2	0.52
10.00	-15.00	2	0.61
9.00	-10.00	2	0.67
8.00	-10.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.00	-10.00	2	0.92
3.00	-10.00	2	0.96
2.00	-10.00	2	0.98
1.00	-10.00	2	1.00
0.00	-10.00	2	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00
1.00	10.00	2	1.00
2.00	10.00	2	0.98

3.00	10.00	2	0.96
4.00	10.00	2	0.92
5.00	10.00	2	0.88
6.50	15.00	2	0.81
7.00	5.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67
10.00	10.00	2	0.61
11.00	10.00	2	0.55
31.00	200.00	3	0.01
41.00	100.00	3	0.00
31.00	-100.00	1	0.01
25.00	-60.00	1	0.04
20.00	-50.00	1	0.14
15.00	-50.00	1	0.32
12.00	-30.00	1	0.49
13.00	10.00	2	0.43
14.00	10.00	2	0.38
15.00	10.00	2	0.32
16.00	10.00	2	0.28
17.00	10.00	2	0.24
18.00	10.00	2	0.20
19.50	15.00	2	0.15
20.00	5.00	2	0.14
22.00	20.00	3	0.09
19.00	-30.00	1	0.16
18.00	-10.00	2	0.20
17.00	-10.00	2	0.24
16.00	-10.00	2	0.28
15.00	-10.00	2	0.32
8.50	-65.00	1	0.70
1.00	-75.00	1	1.00
12.00	110.00	3	0.49
11.00	-10.00	2	0.55
10.00	-10.00	2	0.61
9.50	-5.00	2	0.64
8.00	-15.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.00	-10.00	2	0.92
3.00	-10.00	2	0.96
2.00	-10.00	2	0.98

1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
4.00	40.00	3	0.92
3.00	-10.00	2	0.96
2.00	-10.00	2	0.98
1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00
1.00	10.00	2	1.00
2.00	10.00	2	0.98
3.00	10.00	2	0.96
4.00	10.00	2	0.92
5.00	10.00	2	0.88
6.00	10.00	2	0.84
7.00	10.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67
10.00	10.00	2	0.61
11.00	10.00	2	0.55
31.00	200.00	3	0.01
41.00	100.00	3	0.00
31.00	-100.00	1	0.01
25.00	-60.00	1	0.04

20.00	-50.00	1	0.14
15.00	-50.00	1	0.32
12.00	-30.00	1	0.49
12.00	0.00	2	0.49
11.00	-10.00	2	0.55
10.00	-10.00	2	0.61
9.00	-10.00	2	0.67
8.00	-10.00	2	0.73
7.00	-10.00	2	0.78
6.00	-10.00	2	0.84
5.00	-10.00	2	0.88
4.00	-10.00	2	0.92
3.00	-10.00	2	0.96
2.00	-10.00	2	0.98
1.00	-10.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
1.00	0.00	2	1.00
2.00	10.00	2	0.98
2.00	0.00	2	0.98
0.00	-20.00	1	1.00
0.00	0.00	2	1.00
0.00	0.00	2	1.00
1.00	10.00	2	1.00
2.00	10.00	2	0.98
3.00	10.00	2	0.96
4.00	10.00	2	0.92
5.00	10.00	2	0.88
6.00	10.00	2	0.84
7.00	10.00	2	0.78
8.00	10.00	2	0.73
9.00	10.00	2	0.67
10.00	10.00	2	0.61
11.00	10.00	2	0.55
12.00	10.00	2	0.49

APPENDIX B

Partial source code of Bayesian implementation in C/C++:

```
/*****************************************************************
/*     $System:   MASc. Thesis - Intelligent Traction Control System $
/*     $Author:   Kourosh R. Noori $
/* $Supervisor:   Dr. K. Jenab, P.Eng. $
/*   $Workfile:   Bayesian Traction_Main.c  $
/*       $Date:   April 2009  $
/*   $Revision:   1.0  $
*****************************************************************/

/* Standard Header inclusion */
#include <stdlib.h>
#include <stdio.h>
#include <time.h>

/* Project Header Inclusion */
#include "Traction_Parameters.h"
#include "Traction_header.h"

/* External Variables declaration */
extern FILE* mt_OutPutFilePtr;

/* Training data matrix including speed and traction condition */
double Training_Data_Matrix[NUM_RECORDS][NUM_COLUMNS];

/* Input data matrix (speed) which to be classified */
double Input_Data_Matrix[NUM_RECORDS][NUM_COLUMNS];

/* prior probability variables */
extern double Spin_Prior_P;
extern double Normal_Prior_P;
extern double Slide_Prior_P;

/* Mean variables */
extern double Spin_Mean;
extern double Normal_Mean;
extern double Slide_Mean;

/* Variance variables */
extern double Spin_Variance;
extern double Normal_Variance;
extern double Slide_Variance;


/* Function Declaration */
extern void Process_Training_Data(void);
extern void Classify_Input_Data(void);

int main(int argc,  char* argv[])
{
```

```
   /* Local Variables Declaration */
   int i;

   /* Process Training Data */
   Process_Training_Data();

   /* Traction Process Input Data */
   Classify_Input_Data();

   /* Open the output file */
   mt_OutPutFilePtr = fopen ("Traction_Classification_Output.txt",  "w");

   /* see if the module output file is ok */
   if (NULL != mt_OutPutFilePtr)
   {
      fprintf (mt_OutPutFilePtr,
"************************************************************************\n"
);
      fprintf (mt_OutPutFilePtr,  "************************Traction
Classification Results*******************\n");
      fprintf (mt_OutPutFilePtr,
"************************************************************************\n\n"
);

      fprintf (mt_OutPutFilePtr,  " Spin      Prior Probability = %5.2f  +
Mean = %5.2f  +  Variance = %5.2f\n",

Spin_Prior_P,  Spin_Mean,  Spin_Variance);

      fprintf (mt_OutPutFilePtr,  " Normal    Prior Probability = %5.2f  +
Mean = %5.2f  +  Variance = %5.2f\n",

Normal_Prior_P,  Normal_Mean,  Normal_Variance);

      fprintf (mt_OutPutFilePtr,  " Slide     Prior Probability = %5.2f  +
Mean = %5.2f  +  Variance = %5.2f\n\n",

Slide_Prior_P,  Slide_Mean,  Slide_Variance);


      fprintf (mt_OutPutFilePtr,  "\n Legend for classification is as
follows: \n");
      fprintf (mt_OutPutFilePtr,  " 1 = W1 = Spin\n");
      fprintf (mt_OutPutFilePtr,  " 2 = W2 = Normal\n");
      fprintf (mt_OutPutFilePtr,  " 3 = W3 = Slide\n\n");

      fprintf (mt_OutPutFilePtr,  "\n Index          Speed
Classification\n\n");

      for (i=0; i<NUM_RECORDS; i++)
      {
        fprintf (mt_OutPutFilePtr,  "%4d            %5.2f              %d\n",
i,  Input_Data_Matrix[i][0],

(int)Input_Data_Matrix[i][1]);
      }
```

```
      fprintf (mt_OutPutFilePtr,
"\n**********************************\n");
      fprintf (mt_OutPutFilePtr,  "**********    The End    **********\n");
      fprintf (mt_OutPutFilePtr,
"**********************************\n\n");

    } /* end of check for the output file handler */
    else
    {
      printf ("\n Output file can not be handled.\n");
    }

    fclose(mt_OutPutFilePtr);
    return 0;
}
/***************************************************************************/

/* <EOF> */

/*****************************************************************
/*      $System:   MASc. Thesis - Intelligent Traction Control System $
/*      $Author:   Kourosh R. Noori $
/* $Supervisor:    Dr. K. Jenab, P.Eng. $
/*    $Workfile:   Bayesian Traction_Variables.c  $
/*        $Date:   April 2009  $
/*    $Revision:   1.0  $
*****************************************************************/

/* Standard Header inclusion */
#include <stdlib.h>
#include <stdio.h>

#include "Traction_Parameters.h"

/* prior probability variables */
double Spin_Prior_P;
double Normal_Prior_P;
double Slide_Prior_P;

/* number of observation */
int Num_Of_Spin;
int Num_Of_Normal;
int Num_Of_Slide;

/* Mean variables */
double Spin_Mean;
double Normal_Mean;
double Slide_Mean;

/* Variance variables */
double Spin_Variance;
double Normal_Variance;
double Slide_Variance;
```

```
/* External variables declaration */
FILE* mt_OutPutFilePtr;

/* Training data matrix including speed and traction condition */
double Training_Data_Matrix[NUM_RECORDS][NUM_COLUMNS];

/* Input data matrix (speed) which to be classified */
double Input_Data_Matrix[NUM_RECORDS][NUM_COLUMNS];

/*****************************************************************/
/* <EOF> */

/*****************************************************************
/*     $System:   MASc. Thesis - Intelligent Traction Control System $
/*     $Author:   Kourosh R. Noori $
/* $Supervisor:   Dr. K. Jenab, P.Eng. $
/*   $Workfile:   Bayesian Traction_Parameters.h  $
/*       $Date:   April 2009  $
/*   $Revision:   1.0  $
*****************************************************************/
/* Data structur defenition */

/* All traction system definition */
#define  NUM_COLUMNS    (2)    /* number of column in data record */

#define  NUM_RECORDS    (2000)    /* number of data records */

#define  PI   (3.14159265358979323846)     /* Pi number */

/*****************************************************************/
/* <EOF> */

/*****************************************************************
/*     $System:   MASc. Thesis - Intelligent Traction Control System $
/*     $Author:   Kourosh R. Noori $
/* $Supervisor:   Dr. K. Jenab, P.Eng. $
/*   $Workfile:   Bayesian Traction_Input.c  $
/*       $Date:   April 2009  $
/*   $Revision:   1.0  $
*****************************************************************/

#include "Traction_Parameters.h"

/* Input data matrix which to be classified on speed */

/* First column is speed data,  and; */

/* Second column is traction condition as follows: */
/* 0 = W0 = Undefined */
/* 1 = W1 = Spin/Slip */
/* 2 = W2 = Normal */
/* 3 = W3 = Slide */

extern double Input_Data_Matrix[NUM_RECORDS][NUM_COLUMNS] =
{
   0,  0,
   1,  0,
```

```
    2,   0,
    3,   0,
    4,   0,
    5,   0,
    6,   0,
    7,   0,
    8,   0,
    9,   0,

    .
    .
    .
    .
    2,   0,
    4,   0,
    3,   0,
    2,   0,
    1,   0,
    0,   0,
}; /* 2000 records */

/**************************************************/
/* <EOF> */
```

APPENDIX C

Partial source code of fuzzy implementation in C/C++:

```
/*****************************************************************
/*      $System:   MASc. Thesis - Intelligent Traction Control System $
/*      $Author:   Kourosh R. Noori $
/* $Supervisor:   Dr. K. Jenab, P.Eng. $
/*   $Workfile:   Fuzzy Traction_Functions.c  $
/*       $Date:   April 2009  $
/*   $Revision:   1.0  $
*****************************************************************/

/* Standard Header inclusion */
#include <stdlib.h>
#include <stdio.h>
#include <math.h>

/* Project Header Inclusion */
#include "Traction_Parameters.h"

/* prior probability variables */
extern double Spin_Prior_P;
extern double Normal_Prior_P;
extern double Slide_Prior_P;

/* number of observation */
extern int Num_Of_Spin;
extern int Num_Of_Normal;
extern int Num_Of_Slide;

/* Mean variables */
extern double Spin_Mean;
extern double Normal_Mean;
extern double Slide_Mean;

/* Variance variables */
extern double Spin_Variance;
extern double Normal_Variance;
extern double Slide_Variance;

/* Output file */
extern FILE* mt_OutPutFilePtr;

/* Training data matrix including speed and traction condition */
double Training_Data_Matrix[NUM_RECORDS][NUM_COLUMNS];

/* Input data matrix (speed) which to be classified */
double Input_Data_Matrix[NUM_RECORDS][NUM_COLUMNS];

/* Function Definition */
/*****************************************************************/
extern double MaxPosterior(double first, double second, double third)
```

```
{
  double retVal = 0.0;

  if ( first >= second && first >= third )
  {
     retVal = 1;
  }
  else if ( second >= first && second >= third )
  {
     retVal = 2;
  }
  else if ( third >= first && third >= second )
  {
     retVal = 3;
  }
  else
  {
     retVal = 2;
  }

  return retVal; /* this returns the state of nature supposed to be the class
*/
}

/*****************************************************************/
extern double Prior_Probability(int condition)
{
  int i = 0;              /* loop index */
  int j = 1;              /* loop index */
  int observation = 0;    /* number */
  double retVal;

  for (i=0; i<NUM_RECORDS; i++)
  {
    if ( condition == (int)Training_Data_Matrix[i][1])
    {
      observation++;
    }
  }

  if (1 == condition)        /* Spin */
  {
    Num_Of_Spin = observation;
  }
  else if (2 == condition)  /* Normal */
  {
    Num_Of_Normal = observation;
  }
  else if (3 == condition)  /* Slide */
  {
    Num_Of_Slide = observation;
  }

  retVal = (double)observation / (double)NUM_RECORDS;

  return retVal;
}
```

```
/***************************************************************/
extern double Mean(int condition)
{
  int i = 0;              /* loop index */
  int j = 0;              /* loop index */
  int observation = 0;   /* number */
  double sum = 0.0;
  double retVal = 0.0;

  for (i=0; i<NUM_RECORDS; i++)
  {
    if ( condition == (int)Training_Data_Matrix[i][1])
    {
       observation++;
       sum += (Training_Data_Matrix[i][0] - Training_Data_Matrix[i-1][0]);
    }
  }

  if (0 != observation)
  {
    retVal = sum / (double)observation;
  }
  else
  {
    retVal = 0.0;
  }
  return retVal;
}
/***************************************************************/
extern double Variance(int condition)
{
  int i = 0;              /* loop index */
  int j = 0;              /* loop index */
  int observation = 0;   /* number */
  double sum = 0.0;
  double retVal = 0.0;
  double mean = 0.0;

  if (1 == condition)        /* Spin */
  {
    observation = Num_Of_Spin;
    mean = Spin_Mean;
  }
  else if (2 == condition)   /* Normal */
  {
    observation = Num_Of_Normal;
    mean = Normal_Mean;
  }
  else if (3 == condition)   /* Slide */
  {
    observation = Num_Of_Slide;
    mean = Slide_Mean;
  }

  for (i=0; i<NUM_RECORDS; i++)
  {
  if ( condition == (int)Training_Data_Matrix[i][1])
```

```
    {
      sum += ( (Training_Data_Matrix[i][0] - Training_Data_Matrix[i-1][0]) -
mean ) *
              ( (Training_Data_Matrix[i][0] - Training_Data_Matrix[i-1][0]) -
mean );
    }
  }

  if (0 != observation)
  {
    retVal = sum / (double)observation;
  }
  else
  {
    retVal = 0.0;
  }

  return retVal;
}
/*****************************************************************/
extern double Class_Conditional_Probability(double deltaSpeed, int condition)
{
  double ClassConditional = 0.0;
  double retVal = 0.0;

  if (1 == condition)        /* Spin = W1*/
  {
    /* Gaussian distribution */
    ClassConditional = 1/( (double)sqrt(Spin_Variance*2*PI)) *
                       exp(-((deltaSpeed-Spin_Mean)*(deltaSpeed-
Spin_Mean))/(2*Spin_Variance));
  }
  else if (2 == condition)   /* Normal = W2*/
  {
    /* Gaussian distribution */
    ClassConditional = 1/( (double)sqrt(Normal_Variance*2*PI)) *
                       exp(-((deltaSpeed-Normal_Mean)*(deltaSpeed-
Normal_Mean))/(2*Normal_Variance));
  }
  else if (3 == condition)   /* Slide = W3*/
  {
    /* Gaussian distribution */
    ClassConditional = 1/( (double)sqrt(Slide_Variance*2*PI)) *
                       exp(-((deltaSpeed-Slide_Mean)*(deltaSpeed-
Slide_Mean))/(2*Slide_Variance));
  }

  retVal = ClassConditional;
  return retVal;
}
/*****************************************************************/
extern double Evidence(double deltaSpeed)
{
  double sum = 0.0;
  double retVal = 0.0;

  if (0.000001 < Spin_Variance)
```

```
  {
    sum += Class_Conditional_Probability(deltaSpeed, 1)*Spin_Prior_P;
  }

  if (0.000001 < Normal_Variance)
  {
    sum += Class_Conditional_Probability(deltaSpeed, 2)*Normal_Prior_P;
  }

  if (0.000001 < Slide_Variance)
  {
    sum += Class_Conditional_Probability(deltaSpeed, 3)*Slide_Prior_P;
  }

  retVal = sum;
  return retVal;
}
/*****************************************************************/
extern double Postrior_Probability(int condition, double deltaSpeed)
{
  double retVal = 0.0;

  if (1 == condition)        /* Spin = W1 */
  {
    retVal = (Class_Conditional_Probability(deltaSpeed,
1)*Spin_Prior_P)/Evidence(deltaSpeed);
  }
  else if (2 == condition)  /* Normal = W2 */
  {
    retVal = (Class_Conditional_Probability(deltaSpeed,
2)*Normal_Prior_P)/Evidence(deltaSpeed);
  }
  else if (3 == condition)  /* Slide = W3 */
  {
    retVal = (Class_Conditional_Probability(deltaSpeed,
3)*Slide_Prior_P)/Evidence(deltaSpeed);
  }

  return retVal;
}
/*****************************************************************/
extern void Process_Training_Data(void)
{
  Spin_Prior_P = Prior_Probability(1);
  Normal_Prior_P = Prior_Probability(2);
  Slide_Prior_P = Prior_Probability(3);

  Spin_Mean = Mean(1);
  Normal_Mean = Mean(2);
  Slide_Mean = Mean(3);

  Spin_Variance = Variance(1);
  Normal_Variance = Variance(2);
  Slide_Variance = Variance(3);
}
/*****************************************************************/
extern void Classify_Input_Data(void)
```

```
{
  double deltaSpeed = 0.0;
  double PPW1 = 0.0;  /* Posterior Probablity for Spin */
  double PPW2 = 0.0;  /* Posterior Probablity for Normal */
  double PPW3 = 0.0;  /* Posterior Probablity for Slide */

  int i = 0;          /* loop index */

  for (i=0; i<NUM_RECORDS; i++)
  {
    if ( 0 == i )
    {
      deltaSpeed = Input_Data_Matrix[i][0];
    }
    else
    {
      deltaSpeed = Input_Data_Matrix[i][0] - Input_Data_Matrix[i-1][0];
    }

    /* Calculate all posterior probabilities */
    if (0.00001 < Spin_Variance)
    {
      PPW1 = Postrior_Probability(1, deltaSpeed);
    }

    if (0.00001 < Normal_Variance)
    {
      PPW2 = Postrior_Probability(2, deltaSpeed);
    }

    if (0.00001 < Slide_Variance)
    {
      PPW3 = Postrior_Probability(3, deltaSpeed);
    }

    /* Set the decesion based on the maximum of the posterior probablity */
    Input_Data_Matrix[i][1] = MaxPosterior(PPW1, PPW2, PPW3);
  }
}
/**************************************************************/
/* <EOF> */

/**************************************************************
/*     $System:   MASc. Thesis - Intelligent Traction Control System $
/*     $Author:   Kourosh R. Noori $
/* $Supervisor:   Dr. K. Jenab, P.Eng. $
/*   $Workfile:   Fuzzy Traction_Variables.c  $
/*       $Date:   April 2009  $
/*   $Revision:   1.0  $
**************************************************************/

/* Standard Header inclusion */
#include <stdlib.h>
#include <stdio.h>

#include "Traction_Parameters.h"
```

```
/* prior probability variables */
double Spin_Prior_P;
double Normal_Prior_P;
double Slide_Prior_P;

/* number of observation */
int Num_Of_Spin;
int Num_Of_Normal;
int Num_Of_Slide;

/* Mean variables */
double Spin_Mean;
double Normal_Mean;
double Slide_Mean;

/* Variance variables */
double Spin_Variance;
double Normal_Variance;
double Slide_Variance;

/* External variables declaration */
FILE* mt_OutPutFilePtr;

/* Training data matrix including speed and traction condition */
double Training_Data_Matrix[NUM_RECORDS][NUM_COLUMNS];

/* Input data matrix (speed) which to be classified */
double Input_Data_Matrix[NUM_RECORDS][NUM_COLUMNS];

/*************************************************************************/
/* <EOF> */

/**************************************************************************
/*      $System:   MASc. Thesis - Intelligent Traction Control System $
/*      $Author:   Kourosh R. Noori $
/* $Supervisor:   Dr. K. Jenab, P.Eng. $
/*    $Workfile:   Fuzzy Traction_Parameters.h  $
/*        $Date:   April 2009  $
/*    $Revision:   1.0  $
*************************************************************************/
/* Data structur defenition */

/* All traction system definition */
#define  NUM_COLUMNS     (2)    /* number of column in data record */

#define  NUM_RECORDS     (2000)  /* number of data records */

#define  PI   (3.14159265358979323846)      /* Pi number */

/**************************************************************************/
/* <EOF> */

/**************************************************************************
/*      $System:   MASc. Thesis - Intelligent Traction Control System $
/*      $Author:   Kourosh R. Noori $
/* $Supervisor:   Dr. K. Jenab, P.Eng. $
/*    $Workfile:   Fuzzy Traction_Input.c  $
```

```
/*      $Date:   April 2009  $
/*   $Revision:   1.0  $
*****************************************************************/

#include "Traction_Parameters.h"

/* Input data matrix which to be classified on speed */

/* First column is speed data,  and; */

/* Second column is traction condition as follows: */
/* 0 = W0 = Undefined */
/* 1 = W1 = Spin/Slip */
/* 2 = W2 = Normal */
/* 3 = W3 = Slide */

extern double Input_Data_Matrix[NUM_RECORDS][NUM_COLUMNS] =
{
    0,   0,
    1,   0,
    2,   0,
    3,   0,
    4,   0,
    5,   0,
    6,   0,
    7,   0,
    8,   0,
    9,   0,
    10,  0,
    11,  0,
    31,  0,
    41,  0,
    31,  0,
    25,  0,
    20,  0,
    15,  0,
    19,  0,

    .
    .
    .
    .

    20,  0,
    22,  0,
    19,  0,
    18,  0,
    17,  0,
    16,  0,
    15,  0,
    8,   0,
    0,   0,
}; /* 2000 records */

/*******************************************/
/* <EOF> */
```

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