

Univariate Analysis for Condition-Based Maintenance: A Case Study

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ABSTRACT

In this paper, we have proposed a Condition-based Maintenance technique for vehicle tire pressure monitoring utilizing univariate statistical analysis. Statistical techniques are very powerful for predicting the future states based on current and previous states of the system or subsystem. Two important statistical techniques ARAR and Holt-Winters have been studied for their robustness to the predictions of such data set. This paper also performs comparative simulation studies to prove the usefulness of both the algorithms based on the data available from wireless sensor nodes. These sensors are directly mounted on tires externally and report the current air pressure to control unit. The control unit performs tire pressure prognosis using univariate statistical technique.

INTRODUCTION

In past few years, accidents due to flat tire drew a significant attention of automobile manufacturers. Every year thousands of car accidents are happening on United States highways due to flat tires [1, 2]. It might happen due to various reasons e.g. defective tire valve, tire puncture, tire cut, poor driving, bad road conditions, etc. Under inflation can cause less fuel economy, death, injuries, and many more. An automated device that can report air pressure warnings on real time basis to the driver so that s/he can take corrective action before tire becomes completely flat, may prove to be safest solution. Although air leaks can be prevented by periodic pressure checks but this may not always be helpful.

There are various maintenance strategies as discussed in [3]. The periodic maintenance approaches are best suited for the maintenance as long as finance is not a concern. Such approaches are expensive, lead to down time for maintenance. On the other hand, condition-based

maintenance approach overcomes the difficulty faced by the periodic maintenances. CBM works on the current condition of the system or sub-system. It analyzes the failure patterns as well as the history of the part or sub-part. Based on the current system conditions and prognostication algorithms, it predicts the future failure states. Final decision is then sent to maintenance personnel and displayed to pre-decided monitors/PDAs/Cell Phones etc along with suggestive actions. Associated triggering system periodically keeps on sending warnings to take the corrective action before failure occurs.

The statistical techniques [4] are very popular and robust approaches for predicting time series data. A four stage CBM application building approach [5] to model this maintenance system is shown in Figure 1. We utilized wireless sensor nodes mounted on tire valves to collect data. These wireless sensor nodes have effective signal range 433 MHz with 200 ft line of site transmission capability. Also, these sensors are cheap and commercially available in the market [6]. One example of such sensor is shown in Figure 2. This wireless sensor can measure up to 199 psi, weighs 6 oz with height and diameter of 2.8 cm, 2.6 cm respectively. Following are the main contributions of this work.

- Real Time data modeling of pressure behavior (trend) for some specific tire i.e. 225/40-18 (18" tire).
- Pre-processing of collected data from the wireless sensors
- Univariate statistical analysis for prognostication of pressure trends
- Comparison of two specific techniques and finding the optimal strategy

- Computation of Distance Vector (DV) for determination of four different pressure levels: Safe, Tolerance, Risk, and Failure zone.
- Advisory generation based on current and future fault conditions.

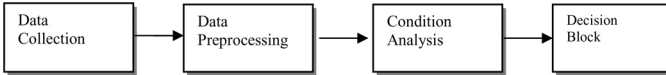


Figure 1. Four Stage Architecture for CBM [4]



Figure 2. Wireless Sensor [5]

BACKGROUND

Various attempts have been made for fault prognostications in literature [7, 8, 9]. Best of our knowledge, univariate analysis is the first attempt to use it for prognosis process in condition-based maintenance that is able to provide very robust results. There are several tire pressure monitoring systems commercially available. Some of the pressure monitoring sensors indicates only whether the pressure is below a threshold. Such systems may not be always helpful while proposed system is highly suitable for reporting the future conditions with high precision. Ferrell [8] presented a strategy for the detection of the abnormal behavior of the system based on the analysis of normal behavior. He proposed a general support vector representation of machine for one-class classification of non-stationary as well as stationary classes. It deals with data even if some classes are missing while regular classification method fails. This method helps to better predict the future health of the system. In [9], the author has presented a generic framework for diagnostics and prognostics. They have designed an online approach which definitely doesn't need to interact with physical system, in turn, saves manpower. This framework is based on multi-basis clustering as well as optimized cluster tracking. It has some drawbacks because of some human decisive factor. Chen et al. [10] presents a closed form analysis for the system when it deviates from the normal course of operation and meets poison's failures. This article focuses on the optimization of the failures. The uptime of the system using polynomial equation based solution is a deterministic and suitable for real life applications.

THEORY

The main focus of this article is to apply appropriate univariate statistical technique to prognosticate the future pressure conditions. This technique uses the current and past pressure samples to compute the rate of pressure drop and

uses univariate statistical technique to predict the pressure and then warn the driver about the problem. In this section, mainly three strategies have been discussed: pressure decay modeling, prognostication algorithm, and distance vector.

A. PRESSURE DECAY

The pressure decay has been modeled using following exponential equation.

$$P_{decay} = P_0(1-r)^{t^{th}} \quad (1)$$

Where P_0 - Initial pressure, psi

P_{decay} - is pressure decay at t^{th} sample, second

r - Rate of pressure decay per sample, psi/10 second

B. STATISTICAL ANALYSIS FOR PROGNOSTICATION

Univariate techniques are very popular for the predictions of time series. Univariate analysis is mainly used for the data that only depends on the single variable. It looks on each variable and range of the values as well as the central tendency of the values. It also focuses on the pattern of response to the variable. In this section, we have used three statistical forecasting techniques discussed in [4] (please refer Chapter 9 for details) for predicting the pressure levels in the future based on past and current values. These are the three techniques,

a. ARAR Algorithm

b. Holt-Winter (HW) Algorithm

I. ARAR. Algorithm

Let raw data collected from the wireless sensors $\{P_t, t=1, 2, \dots, n\}$. This series needs to be transformed to a short memory process, if it doesn't meet the criteria to be short memory process. The transformation is applied iteratively to change from long memory process to short memory process. Usually it requires 2-3 iterations to accomplish this transformation. The series is considered to be long memory process [11], if change in past values affects the current or future values. These processes are divided into three categories long (L) moderately long (M) and short (S) memory processes. Following transformations are applied if process is not short memory process.

a. Apply $\tilde{P}_t = P_t - \hat{\phi}_1 P_{t-1}$, if P_t is L or

b. Apply $\tilde{P}_t = P_t - \hat{\phi}_1 P_{t-1} - \hat{\phi}_2 P_{t-2}$, if P_t is M.

Where $|\hat{\phi}| < 1$, τ is lag, and $\hat{\tau}$ is value of τ that minimizes

$Err(\tau)$.

$$Err(\tau) = ERR(\hat{\phi}(\tau), \tau) \quad \text{and}$$

$$ERR(\phi, \tau) = \frac{\sum_{t=\tau+1}^n [P_t - \phi P_{t-\tau}]^2}{\sum_{t=\tau+1}^n P_t^2} \quad \text{where } \hat{\phi}(\tau) \text{ is value of } \phi \text{ that minimizes } ERR(\phi, \tau).$$

The criteria for deciding L, M, or S is described in chapter 9 of reference [3].

In this stage, we fit the Subset AR model to the memory shortened data with different lags $1, \tau_1, \tau_2, \tau_3$ such that $1 < \tau_1, < \tau_2, < \tau_3, \leq m$. We have chosen $m=13$. The lags τ_1, τ_2, τ_3 and corresponding model parameters are estimated either by minimizing σ^2 , or maximizing the Gaussian likelihood using Yule-Walker equation. Now the fitted model can be used to forecast the series that takes the form as shown below,

$$\xi(B)P_t = \phi(1)\bar{P}_t + W_t \quad (2)$$

Where W_t is White Noise (WN) term, and $\xi(B)$ is whitening filter.

We can compute root means square error to measure the accuracy of the prediction i.e.

$$RMSE = \sqrt{\sum_{i=1}^i (P_{n+i} - Q_n P_{n+i})^2 / n} \quad (3)$$

Where Q_n is predictor, n is number samples, and i is number of values to be predicted. Lower the RMSE, higher the precision.

II. Holt-Winter Algorithm

HW algorithm is primarily suitable for series that have a locally linear trend without periodic fluctuation (also called seasonality). The main idea is to allow for a time-varying trend by specifying the forecasts. This method learns the trends of the series to predict the values. It also computes weighted-average of predicted and observed values to smoothen the trends iteratively. Finally, we calculate RMSE using [equation \(3\)](#).

C. DISTANCE VECTOR

The distance vector [12] method has been used to identify the various pressure levels. Such methods are more effective for the fluctuating air pressures i.e. pressure change with time.

But it is also useful for the random pressure change that has little larger P-F interval. The P-F interval is the time between when pressure starts changing significantly and goes below the predefined threshold. This is the interval where all analysis and prognostications are done. The distance vector is another metric to identify the pressure levels which is set of deviations of pressure levels from normal condition at different time of pressure measurements. It helps in dividing pressure levels into different zones. The vector values can be negative or positive depending upon the under or over damping i.e. negative when measured pressure level is below the tolerance and positive when above the tolerance. Various pressure patterns can be computed by using multiple distance vectors. These pressure patterns can be used to prognosticate the future system failures. Pressure levels are divided into four main categories: Safe zone, Tolerance zone, Risk (warning) zone, and Failure zone. The pressure levels within the tolerance region are acceptable. When pressure level reaches in risk zone, CBM system starts sending warnings to maintenance center and corrective action must be taken before reaching to failure zone. Such maintenance system saves from serious accidents as well as from the unexpected down time.

Let P_s is standard pressure level recommended by tire manufacturer and P_t is observed pressure levels at discrete time intervals then distance vector, D_t can be computed by [equation \(4\)](#)

$$D_t = P_s - P_t \quad (4)$$

Safe zone is considered to be a pressure level is within 0-10% of recommended range of tire manufacturer for specific tire. Tolerance zone is when tire pressure lies within 10-25% of recommended range. The risk zone starts from 25% and spans till 35% while failure zone is above 35% of recommended range. These are our design assumptions not the standard criteria and it is adjustable as per optimization requirements.

SIMULATION

The simulation model has been divided into stage: Data generation and analysis stage. The data generation is modeled using simulated wireless sensor nodes directly mounted on the wheel valve. Samples have been collected every 10 seconds from the two front tires. Every sensor node contains a unique identifier that is transmitted along with each packet transmitted. These sensors are capable to preprocess the data and can send numerical value in *kPa* and *psi*. Pressure data has been modeled using real life scenarios from the articles in [13]. We started the observations with atmospheric temperature about 65 ± 5 °F since morning after stabilizations over night. Initially, temperature increases about 1 psi every 5 minutes for 20 minutes and then 1 psi for next 20 minutes and