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GASOLINE ENGINE INTAKE MANIFOLD LEAKAGE DIAGNOSIS/PROGNOSIS USING HIDDEN MARKOV MODEL

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Abstract. *Leakages in the air intake system (AIS) of gasoline engine can deteriorate its performance causing poor fuel efficiency, air pollution and retarded driving performance. The diagnosis and prognosis of air leakage becomes inevitable in order to enhance reliability and improve fuel consumption. Currently, air leakages detection is hardly found in any of the available On Board Diagnostic version-II (OBD-II) scanners. In this paper, a challenging task of detecting manifold air leakage at early stage has been resolved by employing discrete Hidden Markov Model (HMM). Discrete HMM is an stochastic classifier that has been exploited for the first time to generate useful information about AIS condition based maintenance. The proposed fault diagnosis and prognosis (FDP) scheme can detect air leaks and consequently the severity of air leakage is explored to update the schedule of maintenance prior to any mishap. The validation of the proposed algorithm is carried out on 1.3L production vehicle engine. The experimental results demonstrate that HMM based FDP scheme accurately detects air leakage at early stage and informs about its approximate severity. The suggested scheme for leakage diagnosis is cheaper, does not require any extra hardware installations and it remains valid for all OBD-II compliant commercial vehicles.*

1. **Introduction.** On-board condition monitoring of naturally aspirated automotive engines is an integral part of Electronic Control Unit (ECU) equipped vehicles. This is because of strict legislative regulations defined in OBD-II [1] and European On-Board Diagnostics. Automotive industry is constantly struggling to incorporate efficient on-board fault diagnosis methodologies to overcome these legal requirements. Besides such requirements, end-user satisfaction is also a major concern of automotive industry. Fault free, fuel efficient and environmental friendly vehicles are always preferred.

One of the main requirements of ODB-II for spark ignition (SI) engine is to monitor the health of its AIS. Any OBD-II compliant vehicle will be equipped with Manifold Air Pressure (MAP) or Manifold Air Flow (MAF), throttle position and angular speed sensor. These sensors provide useful information to monitor the health of air intake system and to diagnose/prognose malfunctioning of the components involved in AIS. The components are air filter, intake manifold, throttle valve and installed sensors. A brief discussion will give us an overview of the problems caused by AIS malfunctioning, its effect on engine performance and how the researchers attempted to resolve the problem.

1.1. **Air intake system fault diagnosis/prognosis.** Engine fuel efficiency depends on the Air to Fuel Ratio (AFR) of in-cylinder mixture that is required to be as close to its stoichiometric proportions as possible. The standard stoichiometric ratio can be maintained if AIS performance is ensured. Any malfunction in AIS will affect the amount of oxygen required for complete combustion, thus disturbing stoichiometric proportion. One of the main factors that retard fuel efficiency is leakages in inlet manifold. Air leakages in inlet manifold increase the amount of uncontrolled oxygen for combustion process, and this may result in high engine rotational speed and unpredictable manifold pressure. This malfunctioning may let end-user experience hissing noise, engine stumbling, rough/fast idling or stalling, poor gas mileage and hesitation/poor pickup.

However, in actuality air leakages force MAP/MAF sensor to generate false measurements that can result in deviation in AFR, that may cause emissions to increase (Pollution), lean or rich air fuel mixture, that may cause misfire (Rough Idle/Hesitation) and loss of generated power, that may effect the quality of drivability (Engine Stumbling, etc.). These symptoms are visible only after air leakage has occurred. The possible causes of manifold leakages can be aging effects of hoses connecting manifold to other components like Exhaust Gas Recirculation (EGR) hose, power brake booster hose. Other causes may include EGR valve leaks, intake manifold gasket leaks, aging of throttle/butterfly valve and other gaskets leaks. Figure 1 gives a brief idea of components attached to AIS, that can cause air leakage. Besides leakage in AIS, components in connection with manifold, if got ruptured, may cause air leaks too. For example, any damage to power brake booster can cause air leakage in manifold.

Therefore, in order to avoid such situations early diagnosis/prognosis of air leakages becomes inevitable. Currently, automotive industry utilizes many experience and lookup tables based techniques to monitor AIS health. As a consequence the available ODB-II scanners are unable to detect manifold leakages. However, several researchers have developed methodologies to avoid above highlighted scenarios caused by manifold air leakages. Nyberg et al. [2] identified manifold air leakage by proposing a physical model of air leaks for turbo charged engine whose parameters were identified by Recursive Least Squares (RLS). The identified parameters helped to check the severity of leakages. Dutka et al. [3] presented mathematical model of an internal combustion engine to detect failures in the intake manifold. The proposed fault detection and isolation method performed threshold tests on the directional residuals. The residuals were generated by a combination of a state-dependent Kalman filter, an open-loop observer and an unknown input estimator. Franchek et al. [4] suggested diagnostic approach for air leakage based on a static air path model, which was adapted online such that the model output matches the measured output during steady state conditions. The resulting changes in the model coefficients create a vector whose magnitude and direction were used for fault detection and isolation. Sangha et al. [5] proposed Radial Basis Function (RBF) neural network based diagnosis scheme for air leakages. MVEM was used to simulate air leaks and other faults to validate

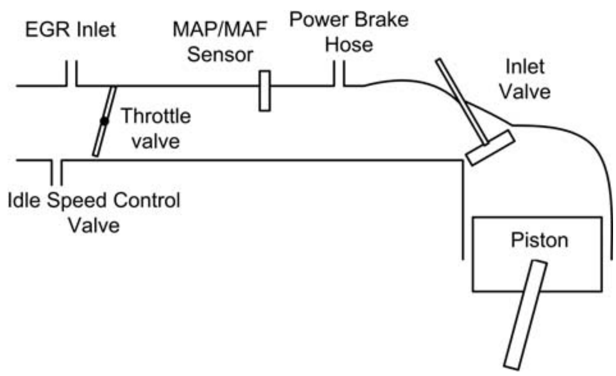

FIGURE 1. Schematic diagram of AIS showing connecting components that may contribute in air leaks

the scheme. The authors in [6], proposed classifier fusion approach for diagnosis of automotive systems. The methodology validation was limited to synthetic faults generated by Computer aided multi-analysis system in Hardware In Loop Simulations (HILS).

It can be observed that an air leakage detection scheme compliant to OBD-II standards is hardly available in literature. This time the authors propose a Hidden Markov Model based scheme to detect manifold leakages for the first time. The key feature of the proposed scheme is its compliance to OBD-II standards. The suggested HMM based FDP scheme requires pressure and crankshaft sensor measurements acquired from OBD-II scanner. Thus, the scheme can be incorporated in any OBD-II compliant scanner software. This feature makes the scheme cheaper and readily implementable on any ODB-II compliant production vehicle. Unlikely, other manifold leakage diagnosis schemes as discussed above, were limited to simulated or synthetic data generated by HILS. Other suggested methodologies involve lab setup of an engine equipped with expensive instrumentation and data acquisition cards. These aspects make current schemes more costly and applicability of the schemes on production vehicles becomes difficult.

1.2. **Hidden Markov model for fault diagnosis/prognosis.** Fault diagnosis is an active research area focused by many researchers [7, 8, 9, 10]. Among various faults diagnosis techniques, Hidden Markov Model has successfully proved its diagnosis capability [11]. Hidden Markov Model is a statistical tool for modeling a wide range of time series data. This powerful statistical tool is used for modeling generative sequences that can be characterized by an underlying process producing an observable sequence. HMMs have found application in many areas of signal processing like Speech recognition [12]. Besides its application in signal processing, HMM is extensively used for estimation, Condition Based Monitoring (CBM), fault diagnosis and prognosis of engineering systems [11]. For ball bearing, Ocak and Loparo [13] introduced fault detection and diagnosis scheme based on its vibration signals classification by HMM. The extracted features from amplitude demodulated vibration signals were used for online health monitoring of bearing of an induction motor driven mechanical system. Similarly, Kwan et al. [14] proposed HMM based fault diagnosis methodology for monitoring ball bearing health. Principal Component Analyzed (PCA) sensor data was used to generate codebook. The classified HMM by the diagnosis scheme was investigated for fault prognosis. Zhang et al. [15] suggested Remaining Useful Life (RUL) of ball bearings based on health degradation index returned by HMM classifier. For machine tools FDP, Baruah et al. [16] employed sensor signals from machine tools to analyze their health through HMM. For FDP in process industry, Dong et al. [17] suggested hidden semi-markov model based framework for diagnosis and prognosis. The authors predicted RUL of pumps through the proposed methodology. The authors in [18] proposed HMM based algorithm for fault diagnosis with partial and imperfect tests. Y. Xu et al. [19] presented an intelligent fault diagnosis system based on HMM for process industry operations. The wavelet packet technique based extract features served as input for HMM based classifier. The authors in [20] proposed an approach combining variable moving window and HMM for online identification of abnormal operating conditions for Tennessee Eastman process. Bakhtazad et al. [21] combined wavelets with HMM to detect abnormal behavior. Wavelets were used to generate the features, and HMM was used for classification.

From the above discussion, it is clear that HMM is extensively used in industry for FDP of various engineering systems, due to its low computation cost and ease of implementation. However, this is the first time that discrete HMM based fault classifier is proposed for naturally aspirated automotive engine AIS. Currently, the proposed FDP scheme is focused on air leakages detection; however, the scheme can be extended to monitor other faults as well. The implementation results demonstrate accurate diagnosis and prognosis of incipient and abrupt air leakage in pressure manifold. Another aspect of the proposed scheme is its prognostic framework, that helps to predict the leakages status in order to ensure better fuel mileage and smooth driving.

Rest of the paper is organized as follows. Section 2 explains how air intake system is modeled under discrete HMMs and the properties of HMM required to exploit in order to generate useful information about health status. Section 3 describes the overall methodology for AIS FDP. The experimentation and validation of FDP algorithm is explained in Section 4. Section 5 contains the concluding remarks of the authors, followed by references.

2. **Hidden Markov Model for AIS.** The main reasons for employing HMMs in fault diagnosis of engineering systems are as follows. HMM is capable of characterizing a doubly embedded stochastic process with an underlying stochastic process (hidden faulty system) that, although unobservable, can be observed through another set of stochastic processes (observations from sensors) [18]. The key problem in diagnosis is to choose the most likely hidden state sequence, given the sequence of uncertain observations from installed sensors. HMM is a parametric model containing state transition probabilities. These parameters can be adaptively updated by the well-known Baum-Welch algorithm [12]. Therefore, HMM provides a theoretical platform for a diagnosis scheme, capable of generating the most likely faulty state sequence, while estimating model parameters within the same theoretical framework. A theoretical overview will give the idea how HMM is used for AIS health monitoring.

Hidden Markov Model is characterized by N hidden states of the model. For FDP scheme explained in Section 3, three HMMs are employed to classify the health of AIS, as it can be categorized as healthy AIS, Air leakage in manifold and other faults that can be due to MAP sensor malfunctioning, etc. Each HMM defined for specific health condition contains 4 hidden states. These four hidden states correspond to fault free stage, intermediate fault Stage 1, intermediate fault Stage 2 and faulty stage.

The 4 hidden states in HMM for air leakage in manifold correspond to leakage area in intake manifold. For the ease of visualization and comparison purposes, the leakages have been quantified according to wide open throttle (WOT). The available throttle body diameter, when the throttle valve is fully opened, is $5.4cm$ and this condition is typically termed as WOT. The leakage is usually caused by hoses connecting manifold to other automobile components as discussed earlier. The typical diameter of these hoses range from $.1cm$ to $1cm$. Therefore, the hidden states in HMM for air leakage can be defined as

- State 1 (s_1) for no air leakage (0% of WOT)
- State 2 (s_2) for air leakage of $.25cm$ (4.5% of WOT)
- State 3 (s_3) for air leakage of $.5cm$ (9% of WOT)
- State 4 (s_4) for air leakage of $1cm$ (18% of WOT)

s_4 corresponds to major air leakage that cannot be ignored, whereas s_2 and s_3 are minor intermediate leakage stages, that remain unnoticed by end-user and can be tolerated.

Remark 2.1. *As the hidden states are chosen according to the system under consideration, an optimum number of hidden states has been selected as* 4 *to quantify the health status of intake manifold. For large number of hidden states, one tends towards over-fitting, loss of generalization and computationally extensive algorithm. Any leakage in manifold will be accurately diagnosed and approximately quantified by* 4 *states HMM for air leakage. The quantified status will let the end-user know the severity of air leak.*

The transition probability distribution among these states is defined by $A = [a_{ij}]$, where

$$a_{ij} = P[q_{t+1} = s_j | q_t = s_i] \quad 1 \leq i, j \leq N \tag{1}$$

where q_t is actual state at time t. M observation symbols are defined per state. For the proposed FDP methodology, M corresponds to the size of the codebook generated through vector quantization. The observation symbol probability distribution in state j is given by $B = b_j(k)$, where

$$b_j(k) = P[v_k \; at \; t | q_t = s_j] \quad \begin{array}{l} 1 \leq j \leq N \\ 1 \leq k \leq M \end{array} \tag{2}$$

where v_k is the k^{th} observation symbol. The last requirement to define an HMM is initial state distribution $\pi = [\pi_i]$, where

$$\pi_i = P[q_1 = s_j] \quad 1 \leq j \leq N \tag{3}$$

Therefore, for given N and M, we can use a compact notation to define an HMM as

$$\lambda_c = (A_c, B_c, \pi) \tag{4}$$

where A_c and B_c bear the structure according to pre-defined applications and $c = 1, 2, 3, \ldots$ is the number of HMMs defined for each health status.

2.1. **Choice of HMM.** For FDP through HMM, Bakis or Left-Right Model provides the best logical grounds. The underlying fault propagation sequence is associated with the property that as time increases the fault grade may increase (or stays the same), i.e., the transition is always from left to right. The fundamental property of all Bakis HMMs is that the state transition coefficients have the property

$$a_{ij} = 0 \quad j < i \tag{5}$$

Another constraint on A defined by Bakis Model is

$$a_{ij} = 0 \quad j > i + \Delta \tag{6}$$

where Δ is the maximum number of jumps between the hidden states. With these constraints, the structure of A_c for AIS FDP with $\Delta = 2$ comes out to be

$$A_c = \begin{bmatrix} a_{11} & a_{12} & a_{13} & 0 \\ 0 & a_{22} & a_{23} & a_{24} \\ 0 & 0 & a_{33} & a_{34} \\ 0 & 0 & 0 & a_{44} \end{bmatrix} \tag{7}$$

Figure 2 gives a visualization of HMM used for FDP with the above defined constraints. It can be observed that air leakage, if evolved, will remain constant or increase with time.

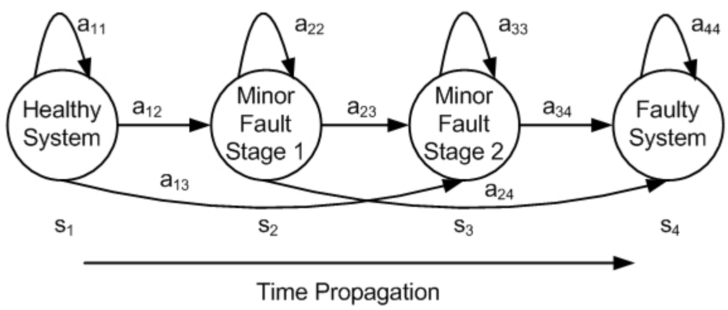

FIGURE 2. Bakis model used for air leakage diagnosis and prognosis

The corresponding stages of leakages (Hidden States) can be seen in Figure 5 on Page 4670.

The defined HMMs will be helpful in decoding the observation sequence $O = O_1, O_2, \ldots, O_T$ (sensor measurements) by relating it to hidden states of each HMM. This can be done by resolving three basic steps associated with HMM, i.e., Evaluation, Decoding and Learning.

2.2. **HMM evaluation.** For given HMM models and sequence of observations, to compute the probability that the observed sequence was produced by which HMM. This is resolved by the *Evaluation* procedure defined for HMM. *Forward Backward algorithm*, is used for the evaluation of HMMs [12]. For the given observation sequence (codebook generated by Vector Quantization (VQ)), $P(O|\lambda_c)$ gives the measure of how close is the observation 'O' to the given model 'λ_c' that is trained for specific health status. $P(O|\lambda_c)$ can be calculated as

$$P(O|\lambda_c) = \sum_{i=1}^{N} \alpha_t(i)\beta_t(i) \tag{8}$$

where the *forward* variable $\alpha_t(i)$ is defined as $\alpha_t(i) = P(O_1, O_2, \ldots, O_t|q_t = s_i, \lambda_c)$ and it can be calculated as

$$\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(i)a_{ij}\right] b_j(O_{t+1}) \quad \begin{array}{l} 1 \le t \le T-1 \\ 1 \le j \le N \end{array} \tag{9}$$

Similarly, the *backward* variable $\beta_t(i)$ is defined as $\beta_t(i) = P(O_{t+1}, O_{t+2}, \ldots, O_T|q_t = s_i, \lambda_c)$ and it can be calculated as

$$\beta_t(i) = \sum_{j=1}^{N} \beta_{t+1}(j)a_{ij}b_j(O_{t+1})$$
$$t = T-1, T-2, \ldots, 1, \ \ 1 \le i \le N \tag{10}$$

Further details can be found in [12]. Besides evaluating any HMM model, α and β are extensively helpful for HMM decoding and learning.

2.3. **HMM decoding.** Evaluation of HMMs generates an exact solution, but HMM decoding is related to generate optimal hidden state sequence associated with given observation sequence. The probability ($\gamma_t(i) = P(q_t = s_i|O, \lambda_c)$) of being in state s_i at time t, given that the observation sequence O and the model λ_c can be defined under Forward Backward (FB) algorithm as

$$\gamma_t(i) = \frac{\alpha_t(i)\beta_t(i)}{P(O|\lambda_c)} \tag{11}$$

Using $\gamma_t(i)$, we can solve for individually most likely state q_i at time t, as

$$q_t = \underset{1 \le i \le N}{\arg\max} \, [\gamma_t(i)] \quad 1 \le t \le T \tag{12}$$

2.4. **HMM learning/training.** The third requirement is to train model parameters ($\lambda_c = (A_c, B_c, \pi)$) for FDP of AIS. This can be done by giving a finite observation sequence as *training data*. The training data is acquired for different stages of air leakage from OBD-II scanner (More details of data acquisition can be found in Section 4.1). The data constitutes of pressure and crankshaft sensor measurements and was collected under steady state conditions. The leakage was introduced by a hole of 1cm (18% of WOT) in intake manifold. The hole was then reduced to collect data sets of 4 leakage stages identified earlier (Experimental conditions are explained in Section 4.1). As OBD-II scanner provides data at variable sampling rate (Data acquisition rate of available OBD-II scanner software varies between 1.5 to 1.8 seconds), the length of the training data can be quantified by the acquired samples. Each training data set was acquired for 100 to 150 samples for 4 times. Hence, the data contains approximately training 600 samples.

For the training of HMMs, one can choose λ_c such that $P(O|\lambda_c)$ is locally maximized using iterative procedure. These iterative procedures include Baum-Welch/EM (Expectation-Modification) method and gradient methods. Each of the HMM (λ_c) is first initialized with prior knowledge, that can iteratively updated with observation sequence using EM algorithm [12]. Once the HMMs are trained the model parameters for HMM for air leakage (λ_2) converge to

$$A_2 = \begin{bmatrix} 0.9996 & 0.0003 & 0.0001 & 0 \\ 0 & 0.7469 & 0.2421 & 0.0110 \\ 0 & 0 & 0.0516 & 0.9484 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{13}$$

$$B_2 = \begin{bmatrix} 0.981 & 0.019 & 0.0001 & 0 \\ 0 & 0.9973 & 0.0027 & 0 \\ 0 & 0 & 0.7804 & 0.2196 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{14}$$

Now fault diagnosis and prognosis for inlet manifold air leakage can be carried out efficiently.

3. HMM Based Fault Diagnosis and Prognosis.

For diagnosis/prognosis, resolving each of the three steps of HMM can be exploited to generate comprehensive information for AIS health. The learning step is exploited to train three HMMs for AIS fault diagnosis. Later on trained HMMs are used in proposed diagnosis and prognosis methodology.

3.1. Feature selection.

The fore-most requirement of FDP scheme is the selection of features such that the health status can be classified efficiently. In literature, for different applications researchers have selected and extracted feature using wavelets, PCA, etc. In air intake system, among various features like mass air flow, manifold pressure, angular speed, throttle position and load torque, manifold pressure and angular speed of engine carry necessary information for the classification of AIS health. The increase in leakage diameter enhances uncontrolled amount of air to enter into combustion chamber, this results in high engine angular speed. Therefore, these features without any transformation can be utilized to generate codebook through vector quantization. Figure 5 on Page 4670 shows the feature vectors facilitating in the identification of clusters for various stages of air leaks. The throttle angle is kept constant at 9.8°, while the pressure and angular speed feature vectors assist to reveal 4 hidden states corresponding to leakages defined in Section 2.

3.2. Preprocessing and codebook generation.

The FDP procedure is designed for active diagnosis under steady state conditions. In order to ensure steady state data, the outliers in acquired data are filtered out before vector quantization. Similarly, transients in the data acquired from OBD-II scanner are processed out to retain the efficiency of the FDP scheme. The preprocessed data is then quantized to generate codebook. VQ is used to generate a code sequence that represents AIS health signature. Using VQ, the scalar data acquired from OBD-II scanner is assigned to a specific region defined by a vector. This assignment results in the generation of code for each sample. The resultant codevectors provide the codebook that can be used as input to discrete HMM based classifier.

3.3. **Diagnosis.** The solution for HMM evaluation is utilized to diagnose air leaks or any other fault in air intake system. Figure 3 describes the steps required to diagnose manifold health.

Measurements from the MAP and crankshaft sensor installed in engine assembly serve as input features for the proposed scheme. These measurements carry stochastic information about the inlet manifold health, that needs to be classified by trained HMMs. After the pre-processing of acquired data from sensors, vector quantization is carried out to generate codebook for the input sequence. This input sequence is supplied to all the three trained HMMs. The trained HMMs are: λ_1 for healthy AIS, λ_2 for AIS with air leakage and λ_3 for AIS with other faults like MAP sensor fault, etc. Each of these HMM will generate $P(O|\lambda_c)$, that will help in measuring how close the observation is to any of the trained HMMs. The index of the maximum $P(O|\lambda_c)$ will diagnose and isolate the system health status. Once the fault is identified, the in-depth analysis of the respective classified HMM will prognoses fault severity.

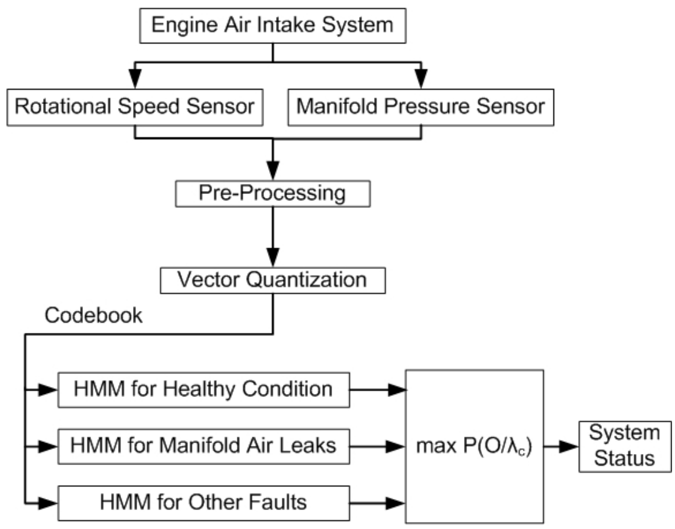

FIGURE 3. Fault diagnosis methodology for air intake system

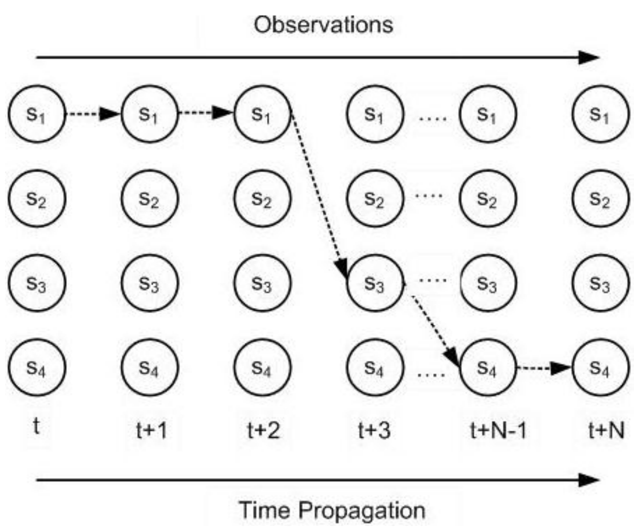

FIGURE 4. Fault propagation through hidden states in classified HMM

3.4. **Prognosis.** Each of the classified HMM by the FDP scheme in Figure 3 comprises of 4 intermediate stages. In Section 2, for λ_2 the corresponding 4 air leakage stages have been identified. One can have more hidden states for precise information but due to reasons in Remark 2.1, the number of hidden states is restricted to four. s_4 is considered as faulty state, that needs to be treated in any case. The intermediate states (s_2, s_3) are either not harmful or not noticed by end-user. Therefore, these intermediate states carry a hidden information about the health of the intake manifold. This information can be captured by *decoding* of HMM. The classified HMM will be decoded to reveal the hidden intermediate fault stage. Figure 4 demonstrates one of the cases that informs how the fault may progress in the system. Any of the intermediate states will predict how near inlet manifold leaks to s_4. This early information of air leaks will let the end-user to decide for maintenance well in time.

4. Experimental Trials.

4.1. **Experimental setup.** The proposed scheme has been applied for the early diagnosis of air leakages in the intake manifold of commercial 1.3L production vehicle engine. The engine is OBD-II compliant ECU. The air intake path of the vehicle is equipped with pressure sensor to measure pressure inside the intake manifold. The pressure is sensed due to change in electrical resistance as the silicon chip in the sensor flexes with variable pressure. The rotational speed of the engine is measured by hall effect based crankshaft sensor. Similarly, throttle valve manipulations can be measured by the installed position sensor. The sensors measurements provide enough information for any leakage in the AIS. Each sensor is communicating with ECU and one can acquire these sensor measurements using OBD-II scanner. The whole communication network is exchanging the information using ISO 9141-2 protocol. The OBD-II scanner connects the computer to ECU using OBD-II cable. By OBD-II scanner, the experiment data can be recorded and analyzed for engine health status. The available ODB-II scanner has variable data acquisition rate with the sampling rate is between 1.5 to 1.8 seconds.

Remark 4.1. *The experimentation for health diagnosis was performed under steady state operating conditions in which each fault (Manifold leakages, pressure sensor fault, etc.) that can occur in engine exhibits uniquely. Usually, engine in idling condition with neutral gear provides the grounds for such diagnosis experimentation. This practice is termed as Active Diagnosis and generally used to execute FDP algorithms* [22].

The experiment was performed during idling as the throttle angle was kept at 9.8° and with neutral gear. No extra loads were induced on engine except the nominal load. The nominal load on engine was around 30% and contributed by: engine rotating mass, e.g., crank shaft, fly wheel, power train components engaged. The operating temperature during the experimentation was around 89°C. The steady state conditions (manifold pressure = 30 kPa and angular speed = 750 − 800 RPM) were ensured during the experiment as coolant fan was in off condition and other disturbances were avoided.

For the training of HMMs, the data was logged with different leakages with aforementioned experimental conditions. As the leakage diameter was increased the angular speed and manifold deviated from their nominal values, though the throttle angle was at 9.8°. Figure 5 shows the actual stages that correspond to hidden states of HMM for air leakage used for training of HMMs. As the data against each leakage is ensured in steady state conditions, this limits the data length to 100 to 150 samples for each stage. Hence, the data contains 600 training samples, as each data set was acquired 4 times.

After the HMMs are trained, the evaluation of the proposed scheme is carried out for three different scenarios.

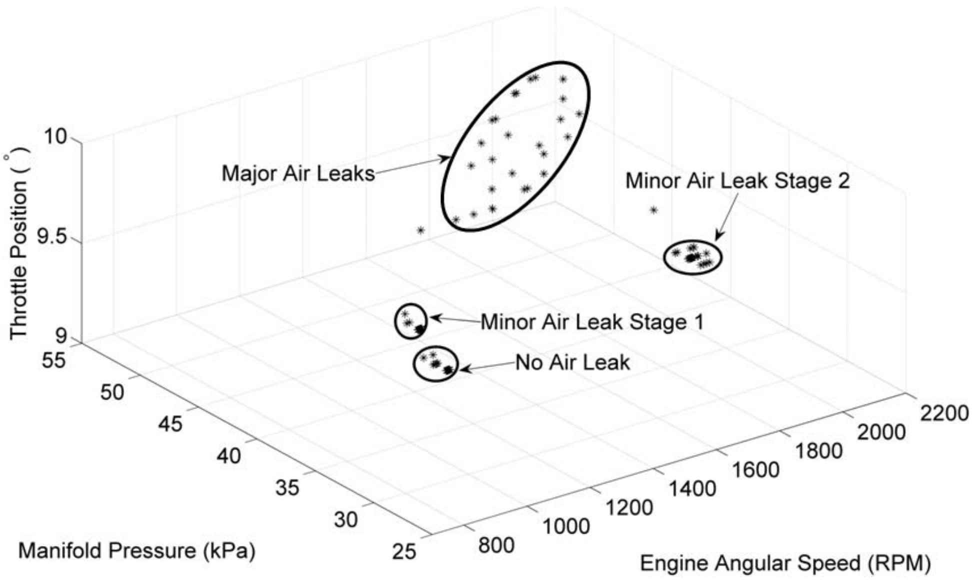

FIGURE 5. Scatter plot of data showing all 4 stages of air leakage

- Normal/ Healthy Inlet Manifold
- Inlet Manifold with Incipient Air Leaks
- Inlet Manifold with Abrupt Air Leaks

4.2. **Healthy air intake system.** By healthy AIS, it is meant that there were no air leaks in the inlet manifold. The data was acquired from OBD-II scanner and fed into FDP scheme. After vector quantization, the codebook was supplied to all the three HMMs. The normalized $P(O|\lambda_c)$ produced by each HMM is shown in Figure 6. It can be observed that HMM for healthy manifold (λ_1) produces maximum value of $P(O|\lambda_1)$, that characterizes the system as healthy. When the scheme has announced the system as healthy, no useful information can be extracted from observing the hidden state sequence of any HMM as there is no air leakage in the manifold.

4.3. **Inlet manifold with air leaks.** In this experiment, the proposed FDP scheme have been evaluated under the presence of air leakages. The respective data can be

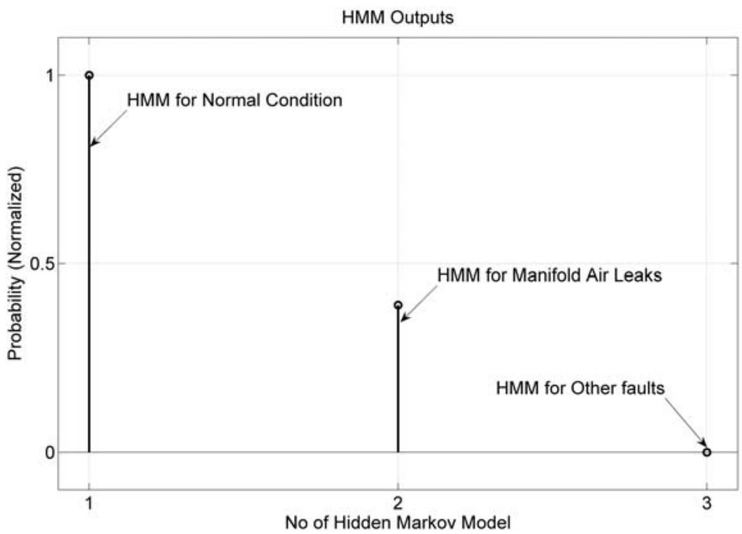

FIGURE 6. Each HMM outcome for healthy intake manifold

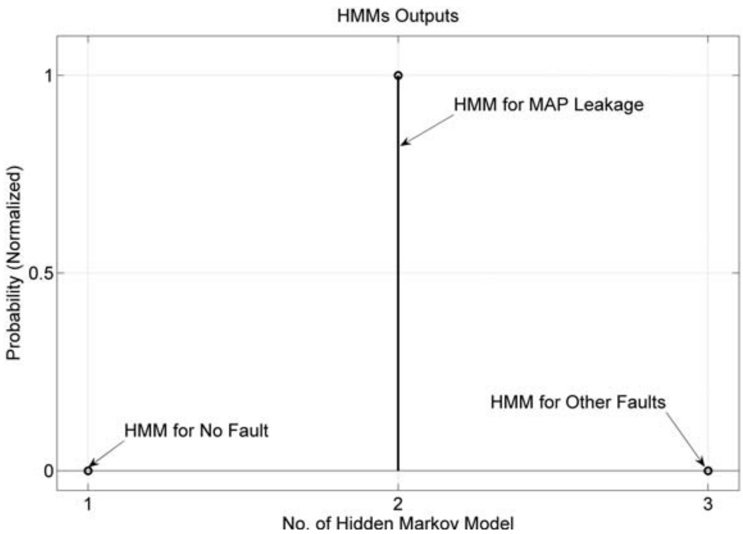

FIGURE 7. Each HMM outcome for inlet manifold leakages

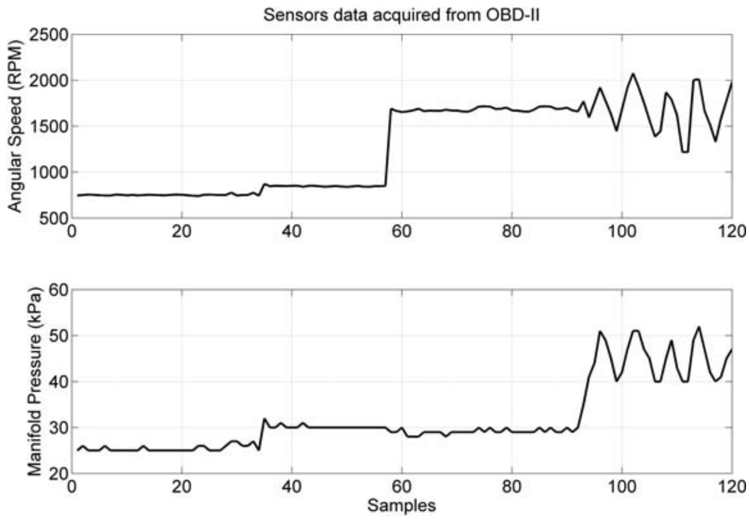

FIGURE 8. Experimental data acquired from 1.3L Honda city engine through OBD-II scanner for incipient air leakages

visualized in Figure 8 and Figure 10. In the first step, the codebook generated by vector quantization of sensor data was used to evaluate HMMs. Figure 7 shows the normalized $P(O|\lambda_c)$ generated by each HMM. It can be observed that in the presence of air leakages, HMM for manifold air leakage (λ_2), produced maximum $P(O|\lambda_2)$. This characterizes the system under faulty status. Once the HMM based classifier has announced the engine inlet manifold as faulty, a detailed investigation of the manifold health becomes mandatory. The in-depth analysis of the faulty system can be carried out keeping in view the nature of fault, i.e., Incipient and Abrupt Fault.

4.3.1. *Incipient air leakages in inlet manifold.* In the first phase of FDP scheme assessment, air leakages were gradually introduced in pressure manifold. This gradual introduction replicates *Incipient Fault* in nature. It was observed in the beginning that minor air leakages of around $1 - 2\%$ of WOT were catered for by ECU installed in the vehicle. It was observed, after a small fluctuation in engine angular speed and manifold pressure, the engine returned to its normal operating condition. But as the air leaks were increased, the engine control unit was unable to handle them. The performance of engine started to

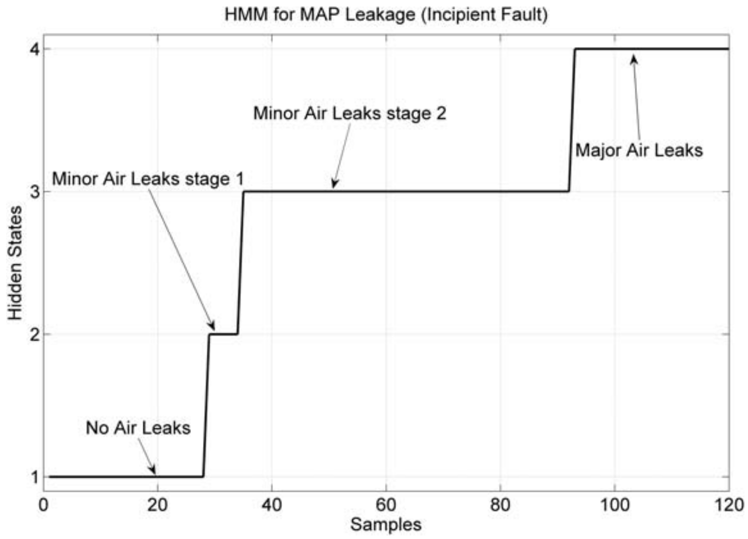

Figure 9. Fault progression in classified HMM, when air leakages were introduced gradually (incipient fault)

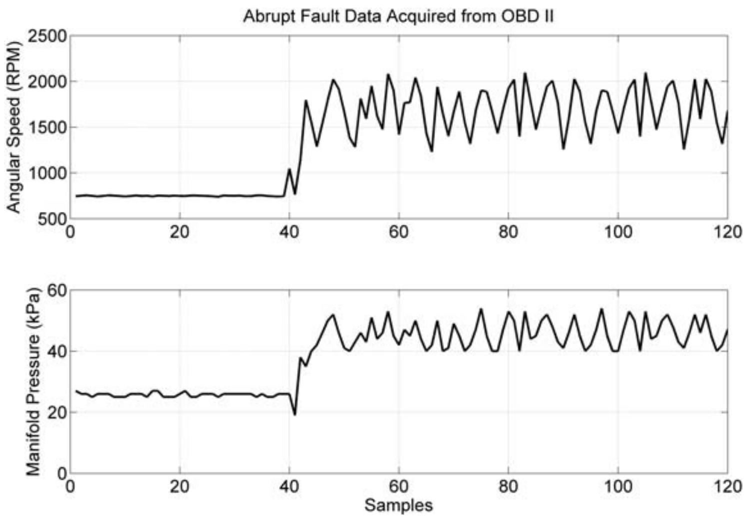

Figure 10. Experimental data acquired from 1.3L Honda city engine through OBD-II scanner for abrupt air leaks

decline. The leakage area was increased until the impaired engine performance was unbearable. This shows that the installed ECU was unable to handle air leaks and detecting air leak at early stage becomes mandatory for engine health.

Remark 4.2. *It can be visualized that when the leakage area was increased at* 58^{th} *sample in Figure 8, the pressure sensor started to generate false readings. One possible reason can be the location of installed sensor is at 6 inches away from the leakage in manifold (One can visualize the leakage location in Figure 1, the leakage was introduced near power brake hose). The performance of the engine started to decline and ECU was unable to detect & announce malfunctioning of engine as malfunction Indication Light (MIL) remained off.*

The experiment data is acquired from the installed sensors through OBD-II scanner as shown in Figure 8. The leakage diameter was approximately increased to $.25cm$ at 34^{th}, $.5cm$ at 57^{th} and $1cm$ at 92^{nd} sample. This data was supplied to FDP scheme in Figure 3. The classified HMM (λ_2) was further investigated for Air Leaks prognosis. Figure 9 demonstrates the incipient fault progression. It can be observed that HMM (λ_2) changes

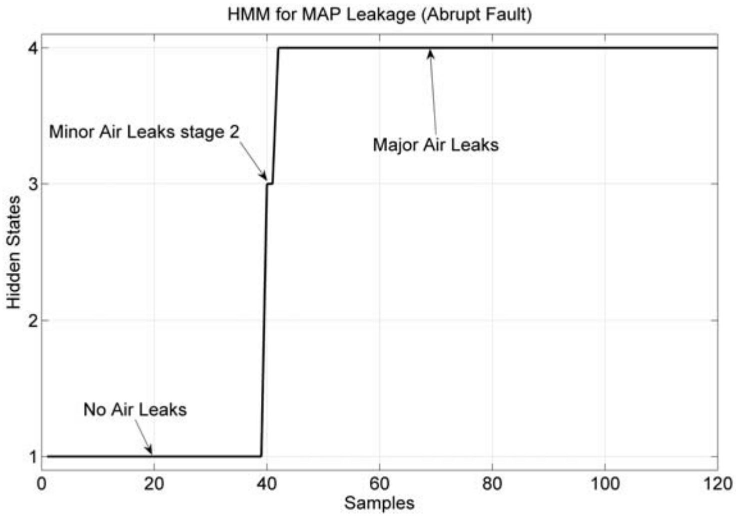

Figure 11. Fault progression in classified HMM, when air leaks were introduced abruptly (abrupt fault)

its states gradually with the increase in air leakage size. One can easily comment that s_2 is unnoticeable/ignorable but once λ_2 is announcing s_3, the end-user can easily be informed about the leakage progression. This practice will help to avoid any serious maintenance expenditures.

Remark 4.3. *It can be seen that the FDP scheme, in the first phase, accurately diagnosed the air leakage in the manifold. However, when the respective HMM* (λ_2) *is analyzed in detail, some of the samples were mis-quantified. This mis-quantification is harmless as the scheme is not declaring the system healthy.*

4.3.2. *Abrupt air leakages in inlet manifold.* In the second phase of FDP scheme testing, air leakage of $1cm$ diameter introduced at 40^{th} sample (Figure 10) crippled engine performance at once. This action replicates *abrupt fault* in nature. The experiment data shown in Figure 10 was acquired from engine rig, that is utilized for the diagnosis and prognosis of abrupt air leaks. The classified HMM from scheme in Figure 3 was explored for fault status, that helped in the prognosis of manifold health. Figure 11 shows in λ_2 the fault traversed from s_1 (Normal Stage) to s_3 (Intermediate Fault Stage 2) and immediately jumps to s_4 (Faulty System). The behavior can be exploited for prognosis as: the moment air leakage of s_3 occurred, it can be informed that an abrupt air leaks have occurred due to any of the reasons outlined in Section 1. Therefore, an immediate checkup is mandatory for the intake pressure manifold.

5. **Conclusion.** In this paper, Discrete Hidden Markov Model is employed for the first time to detect air leakage in pressure manifold at an early stage. The proposed scheme requires measurements from crankshaft and pressure sensor installed in OBD-II compliant vehicle. As the proposed scheme requires data from OBD-II scanner, it can be easily incorporated in any OBD-II scanner software. This attribute makes it cheaper and readily executable for every OBD-II compliant vehicle after minor changes. The sensors data is used to classify AIS health status, after generating a codebook through vector quantization. The classified HMM is further investigated to reveal information that can be helpful for the prognosis of air leaks. A successful validation and experimentation is performed on 1.3L production vehicle engine instead of lab setup. The results demonstrated that the proposed FDP scheme *accurately* categorized and *approximately* quantized the health status of inlet manifold.

REFERENCES

[1] CARB, California's obd-ii regulation, *Section 1968.1, Title 13, California Code of Regulations*, 1993.
[2] M. Nyberg, A. Perkovic and L. Nielsen, Model-based diagnosis of leaks in the air-intake system of an SI engine, *World Congress, SAE*, 1998.
[3] A. Dutka, H. Javaherian and M. Grimble, Model-based engine fault detection and isolation, *American Control Conference*, pp.4593-4600, 2009.
[4] M. A. Franchek, P. J. Buehler and I. Makki, Intake air path diagnostics for internal combustion engines, *Journal of Dynamic Systems, Measurement, and Control*, vol.129, no.1, pp.32-40, 2007.
[5] M. S. Sangha, J. B. Gomm, D. L. Yu and G. F. Page, Fault detection and identification of automotive engines using neural networks, *World Congress, Int. Federation of Automation Control*, 2005.
[6] K. Choi, S. Singh, A. Kodali, K. Pattipati, J. Sheppard, S. Namburu, S. Chigusa, D. Prokhorov and L. Qiao, Novel classifier fusion approaches for fault diagnosis in automotive systems, *IEEE Transactions on Instrumentation and Measurement*, vol.58, pp.602-611, 2009.
[7] J. Wang, B. Jiang and P. Shi, Adaptive observer based fault diagnosis for satellite attitude control systems, *International Journal of Innovative Computing, Information and Control*, vol.4, no.8, pp.1921-1930, 2008.
[8] Y. Wang, W. Wang and D. Wang, LMI approach to design fault detection filter for discrete-time switched systems with state delays, *International Journal of Innovative Computing, Information and Control*, vol.6, no.1, pp.387-398, 2010.
[9] S.-R. Huang, C.-W. Liao, H.-T. Chen and C.-C. Wu, A new method to identify fault current and inrush current on transformer by Jiles-Atherton model, *ICIC Express Letters*, vol.3, no.4(A), pp.897-902, 2009.
[10] M. Takahashi, T. Takagi and Y. Miyawaki, Fault diagnosis of joint-sensors in parallel manipulators, *ICIC Express Letters*, vol.3, no.4(B), pp.1309-1314, 2009.
[11] M. Jager and F. Hamprecht, Principal component imagery for the quality monitoring of dynamic laser welding processes, *IEEE Transactions on Industrial Electronics*, vol.56, pp.1307-1313, 2009.
[12] L. Rabiner, A tutorial on hidden Markov models and selected applications in speech recognition, *Proc. of the IEEE*, vol.77, pp.257-286, 1989.
[13] H. Ocak and K. A. Loparo, Hmm-based fault detection and diagnosis scheme for rolling element bearings, *Journal of Vibration and Acoustics*, vol.127, no.4, pp.299-306, 2005.
[14] C. Kwan, X. Zhang, R. Xu and L. Haynes, A novel approach to fault diagnostics and prognostics, *Proc. of ICRA'03 IEEE International Conference on Robotics and Automation*, vol.1, pp.604-609, vol.1, pp.14-19, 2003.
[15] X. Zhang, R. Xu, C. Kwan, S. Liang, Q. Xie and L. Haynes, An integrated approach to bearing fault diagnostics and prognostics, *Proc. of the 2005 American Control Conference*, pp.2750-2755, vol.4, pp.8-10, 2005.
[16] P. Baruaha and R. B. Chinnama, Hmms for diagnostics and prognostics in machining processes, *International Journal of Production Research*, vol.43, pp.1275-1293, 2005.
[17] M. Dong and D. He, A segmental hidden semi-Markov model (hsmm)-based diagnostics and prognostics framework and methodology, *Mechanical Systems and Signal Processing*, vol.21, no.5, pp.2248-2266, 2007.
[18] J. Ying, T. Kirubarajan, K. Pattipati and A. Patterson-Hine, A hidden Markov model-based algorithm for fault diagnosis with partial and imperfect tests, *Transactions on Systems, Man, and Cybernetics Part C: Applications and Reviews*, vol.30, pp.463-473, 2000.
[19] Y. Xu and M. Ge, Hidden Markov model-based process monitoring system, *Journal of Intelligent Manufacturing*, vol.15, pp.337-350, 2006.
[20] S.-Y. Zhou and S.-Q. Wang, On-line fault detection and diagnosis in industrial processes using hidden Markov model, *Developments in Chemical Engineering and Mineral Processing*, vol.13, pp.397-406, 2005.
[21] A. Bakhtazad, A. Palazoglu and J. Romagnoli, Detection and classification of abnormal process situations using multidimensional wavelet domain hidden Markov trees, *Computers & Chemical Engineering*, vol.24, pp.769-775, 2000.
[22] K. Uwe and N. Lars, *Automotive Control Systems: For Engine, Driveline, and Vehicle*, Springer, 2005.