Fault Diagnosis in Automotive Alternator System Utilizing Adaptive Threshold Method

Ali Hashemi[1], Pierluigi Pisu[2]

[1]Department of Mechanical Engineering, Clemson University, Clemson, SC 29634
ahashem@clemson.edu

[2]Department of Automotive Engineering and CU-ICAR, Greenville, SC 29607
pisup@clemson.edu

ABSTRACT

In this paper, an observer-based adaptive threshold is developed as part of a fault diagnosis scheme to detect and isolate commonly occurring faults in a vehicle alternator system. Since the mathematical model of the alternator subsystem is quite involved and highly nonlinear; in order to simplify the diagnostic scheme, an equivalent linear time varying model based on the input-output behavior of the system is used for threshold equations derivation. A novel approach using Gaussian distribution to obtain the parameters of the system is investigated. The validity of the proposed diagnosis scheme is tested through simulation and the results are presented.

1. INTRODUCTION

Modern vehicles optimal performance is highly dependent of the reliable power generation and storage system (EPGS). Furthermore, most of the modern safety features such as X-by-wire system (Pisu, P., Rizzoni, G., et al. (2000)) are highly dependent on a smooth operation of EPGS systems. Thus, an effective diagnosis algorithm for EPGS system is necessary to maintain the optimal performance of the vehicle. Certain types of faults are commonly occurring in the alternator subsystem, namely belt slip fault, open diode fault, and voltage regulator fault. In this paper, the focus of diagnostic problem is on detecting and identifying these specific set of faults that may occur in the alternator in EPGS systems. In Scacchioli, Rizzoni, and Pisu, (2007) and Scacchioli, Rizzoni, and Pisu, (2006) model-based approaches are used to deal with the problem of fault detection and identification (FDI) for the EPGS system. In Scacchioli at al. (2006), a parity equation approach is used to compare the behaviour of the alternator with the behaviour of the equivalent model and the resulting residual are used in the fault diagnosis algorithm design. In addition, the thresholds are derived statistically to minimize false alarms. Different methods to select the thresholds in fault detection and identification problems can be found in Ding, Guo and Frank, (1993), Ding and Guo, (1996), Emami-Naeini, Akhter, Rock, (1988), Frank, (1990), Hashemi and Pisu, (2011), Li et al., (2007), Pisu, Serrani, You and Jalics, (2006). In this paper, however, a novel method based on observer-based approach to design an adaptive threshold for a linear system with Gaussian distributed parameters is presented. Adaptive threshold changes according to the inputs to the system; thus, it has many advantages over the fixed threshold. In case of the fixed threshold, if the threshold is set too high, sensitivity to fault detection will decrease, whereas if the threshold is set too low, false alarm rate will increase. Adaptive threshold, however, does not have these problems. One downside of using adaptive threshold is its high order. Two approaches for deriving low order threshold approximations and analysis of the trade-off have been recently presented in Hashemi et al., (2011).

This paper is organized as follows. Section 2 describes the model of the system, while in section 3 the problem is formulated. Proposed fault diagnosis scheme is presented in section 4. Section 5 discussed the Gaussian distribution parameters approach. Simulation results are given in section 6. Section 7 presents the conclusion of the paper.

2. MODEL DESCRIPTION

An automotive electric-power generation storage system (EPGS) comprises two basic subsystems, the alternator and the battery, which together supply power to the vehicles electrical loads. The alternator, which is driven by the engine through a belt, provides power to the electrical loads and charges the battery. The battery, on the other hand, provides power when the engine in not running, or when the electrical power demand exceeds the alternator output. The typical alternator for an automotive electrical system comprises the following components:

1) AC synchronous generator
2) Three phase full bridge diode rectifier
3) Voltage regulator
4) Excitation field.

When the engine is running, the alternator AC voltage is rectified through the three phase bridge. The DC output voltage is regulated to be 14.4V. The role of the excitation field is to produce the field current necessary to excite the three-phase synchronous generator.

The details on mathematical model of the alternator can be found in Scacchioli et al. (2006) and details on battery mathematical model can be found in Li, Picciano, Rizzoni, Scacchioli, Pisu, and Salman, (2007).

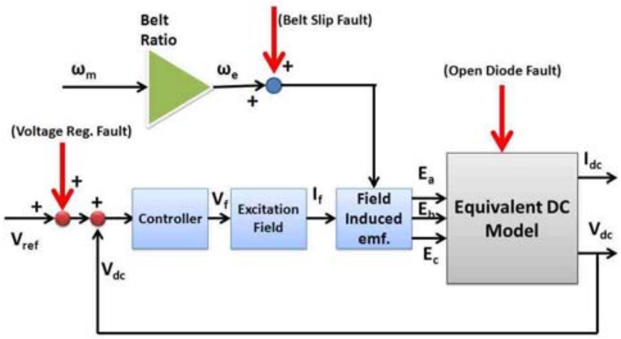

Figure 1. Functional block diagram of the automotive EPGS mathematical model with injected faults.

The mathematical model of the alternator & rectifier is highly nonlinear and complex. In order to obtain a robust diagnosis algorithm, an equivalent simpler model that still describes the behaviour of the original model in terms of input-output relations will be developed. A closer examination of the alternator subsystem shows that the behaviour of the system is functionally similar to that of a DC machine; hence, it can be modelled with an equivalent DC generator model (enclosed in the big rectangle) for the alternator and diode bridge rectifier as shown in Fig. 1 .

The equations of the equivalent model are based on a DC generator, as in Eq. (1), and the equivalent excitation field, as in Eq. (2) and mentioned in Scacchioli, Li, Suozzo, Rizzoni, Pisu, Onori, Salman, and Zhang, (2010) with details.

$$\frac{dI_{dc}}{dt} = -\gamma I_{dc} + \gamma\omega_e + \kappa I_f - \lambda V_{dc} \quad (1)$$

$$\frac{dI_f}{dt} = -\alpha I_f + \beta V_f \quad (2)$$

where I_f is the alternator field current, V_f is the alternator field voltage, I_{dc} is the rectified output current, ω_e is the angular frequency of the alternator, and V_{dc} is the rectified output voltage. The parameters α, β, γ, κ, and λ are functions of ω_e. In order to obtain the variance and mean of these parameters, each parameter variation data with respect to different speed cycles were collected. Afterwards, by fitting the proper Gaussian distribution, the variance and mean of each parameter were estimated. Note that vehicle speed and therefore ω_e can be classified into few different driving behaviours such as city driving, highway driving, cross country, etc., and parameter distributions can be pre-determined in each case. Then, in real-time, a pattern recognition algorithm can be used to identify in which class the current driving belongs therefore selecting the appropriate parameter distributions corresponding to that class.

Equations (1) and (2) in observable canonical form can be written as:

$$\begin{bmatrix} \dot{z}_1 \\ \dot{z}_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & -\alpha\gamma \\ 1 & -(\alpha+\gamma) \end{bmatrix}}_{A_0} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} + \underbrace{\begin{bmatrix} \kappa\beta & \alpha\gamma & -\alpha\lambda \\ 0 & \gamma & -\lambda \end{bmatrix}}_{B_0} \begin{bmatrix} V_f \\ \omega_e \\ V_{dc} \end{bmatrix} \quad (3)$$

$$y = \underbrace{\begin{bmatrix} 0 & 1 \end{bmatrix}}_{C_0} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

where,

$$z_1 = \kappa I_f + \alpha I_{dc} \quad (4)$$

$$z_2 = I_{dc} \quad (5)$$

For the system under consideration in this paper, if for example, we denote αγ as b_{12} (corresponding element in the B matrix in Eq. (3)), the data distribution and its Gaussian fit are shown in Fig. 2.

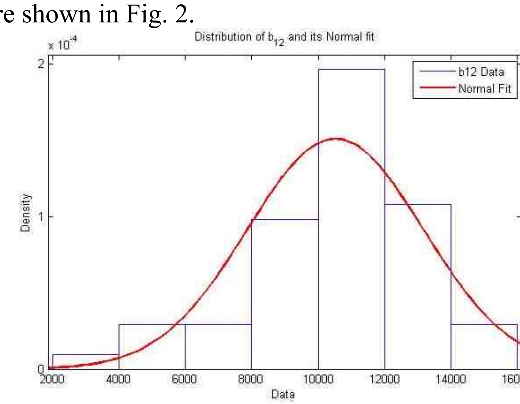

Figure 2.b_{12}(αγ)data distribution and its Normal distribution.

The formulation in Eq. (3) is later used to develop the adaptive threshold equations. In the proposed model, input signals are engine speed ω_e, the alternator voltage V_{dc}, and the excitation field voltage V_f and, alternator current I_{dc} is the output signal. This model is utilized in the design of the diagnosis scheme as described in the following sections.

3. PROBLEM FORMULATION

In this paper, the problem of detection and isolation of commonly occurring fault for the alternator in an EPGS is considered. To find a solution for this problem, a fault diagnostic scheme part of which utilizes observer-based adaptive threshold is developed.

To this end, the following faults are considered in the system:

1) Belt slip fault: It is an input fault that occurs when the alternator belt does not have the proper tension to keep the alternator pulley rotating synchronously with the engine shaft. Its effect is a decrease in alternator output voltage, which the voltage regulator compensates by increasing the field voltage.

2) Open diode rectifier fault: This fault consists of a failure of one of the diodes in the three- phase bridge rectifier, causing unbalance in the bridge by loss of one phase. Characteristics of this type of fault are a large ripple in the output voltage and current.

3) Voltage regulator fault: This fault consists of a reduction in the reference voltage that produces a reduction in the alternator output current.

In the process of developing the fault diagnosis scheme, it is assumed that the faults occur separately. Moreover, to design the observer-based adaptive threshold, the measurable inputs and outputs of the system are defined. The inputs are V_{dc}, V_f, and ω_e, and the output is I_{dc}.

4. FAULT DIAGNOSIS SCHEME

The proposed diagnostic scheme combines observer design and adaptive thresholds in order to detect and isolate the three types of alternator faults (belt slip, open diode, and voltage regulator). Figure 3 shows the overall diagnosis scheme for FDI.

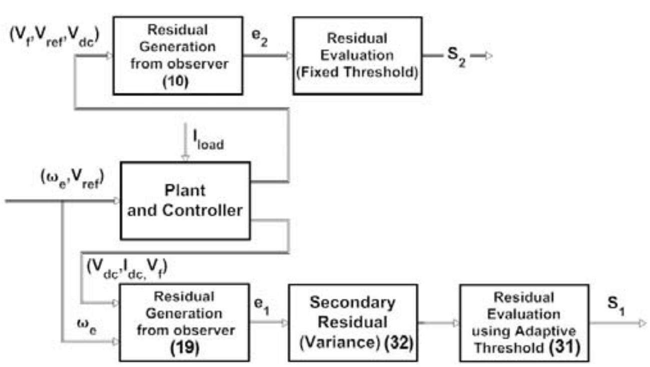

Figure 3. Fault diagnostic scheme.

The diagnostic scheme is comprised of three stages: a primary residual generation, a secondary residual generation, and a residual evaluation. The primary residual generation is constituted by the two observers generating two residuals e_1 and e_2. A third residual is generated from e_1 by a moving standard deviation algorithm which constitutes the secondary residual generation stage. Finally, from the comparison of the residuals with thresholds two signatures S_1, S_2, are generated that represent the residual evaluation stage. The signature S_1 is obtained by comparing the adaptive threshold with the variance of the residual e_1 from the first observer as described in the next section. Signature S_1 alone allows detecting all the previously described faults. For the purpose of isolation of the voltage regulator fault another signature must be introduced, namely signature S_2. The following analysis demonstrates the method utilized to design an observer to isolate the voltage regulator fault. The alternator voltage regulator is implemented as a PI controller, with saturation on V_f that cannot be greater than V_{dc}

$$V_f = sat\left(K_P(V_{ref} - V_{dc}) + sat(K_I \int (V_{ref} - V_{dc}))\right) \quad (6)$$

where K_I, and K_P are the integral and proportional controller gains. Saturation in this case is defined as:

$$\text{if } V_{dc} > V_{ref} \Rightarrow V_f = 0 \quad (7)$$

By defining $U = V_{dc}$-V_{ref}, and the state $x = K_I \int U(t)\,dt$, Eq. (8) away from the saturation of the integral can be represented by

$$\dot{x} = -K_I U \quad (8)$$

$$V_f = sat(x - K_P U) \quad (9)$$

Consider the observer:

$$\dot{\hat{x}} = L(V_f - \hat{V}_f) - K_I U \quad (10)$$

$$\hat{V}_f = \hat{x} - K_p U \quad (11)$$

$$e_2 = V_f - \hat{V}_f \quad (12)$$

By defining $e = \hat{x} - x$, the error dynamics in absence of faults and away from voltage saturation are

$$\dot{e} = L(V_f - \hat{V}_f) = Le_2 = -Le \quad (13)$$

In the presence of a voltage regulator fault, ΔU and no saturation conditions, we have

$$\dot{e} = Le_2 + K_I \Delta U = -Le - (LK_P - K_I)\Delta U \quad (14)$$

$$e_2 = -e - K_P \Delta U \quad (15)$$

which explicitly shows the dependence on the fault. When V_f saturates, nothing can be said about the presence of a fault.

Table 1 summarizes the fault isolation logic for the alternator fault diagnosis scheme. The main assumption in this fault diagnosis scheme is that faults are not occurring concurrently.

Fault type	S1	S2
No Fault	0	0
Belt Slip	1	0
Open Rectifier Diode Fault	1	0
Voltage Regulator Fault	1	1

Table 1. Error signature for the Alternator System

In Table 1, a "zero" means 'residual does not cross the threshold'; while a "one" means 'residual crosses the threshold'. With the current scheme all faults are detectable but belt slip fault cannot be distinguished from diode fault.

5. ADAPTIVE THRESHOLDS IN THE CASE OF GAUSSIAN DISTRIBUTED PARAMETERS

To obtain the signature S_1, an observer-based adaptive threshold is designed based on the state space representation of the equivalent DC generator Eqs. (1) and (2). Details of the derivation for a general case are shown below.

Consider a general state space presentation of a system with n states in observable canonical form:

$$\frac{dz}{dt}=\underbrace{\begin{pmatrix}0&0&\dots&0&-a_0\\1&0&\cdots&0&-a_1\\\vdots&\vdots&\vdots&\vdots&\vdots\\0&0&\cdots&0&-a_{n-2}\\0&0&\cdots&1&-a_{n-1}\end{pmatrix}}_{A_0}z+\underbrace{\begin{bmatrix}b_{00}&b_{01}&\cdots&b_{0,m-1}\\b_{10}&b_{11}&\cdots&b_{1,m-1}\\\cdots&\cdots&\cdots&\cdots\\b_{n-1,0}&b_{n-1,1}&\cdots&b_{n-1,m-1}\end{bmatrix}}_{B_0}u \tag{16}$$

$$y=\underbrace{\begin{bmatrix}0&0&\cdots&1\end{bmatrix}}_{C_0}z \tag{17}$$

where $z\in\mathbb{R}^n, u\in\mathbb{R}^m, y\in\mathbb{R}, A_0\in\mathbb{R}^{n\times n}, B_0\in\mathbb{R}^{n\times m}$, and $C_0\in\mathbb{R}^{1\times n}$. Assuming parameters uncertainties, Eqs. (18) and (19) can be written as:

$$\begin{aligned}\dot{z}&=(A_0+\Delta A_0)z+(B_0+\Delta B_0)u\\y&=C_0z\end{aligned} \tag{18}$$

Notice that $\Delta A_0 z=\Delta\underline{a}y$ with $\Delta\underline{a}=\begin{bmatrix}\Delta a_0&\Delta a_1&\cdots&\Delta a_{n-1}\end{bmatrix}^T$ .An observer can be designed for Eq. (20) as below:

$$\begin{aligned}\dot{\hat{z}}&=A_0\hat{z}+B_0u+L(y-\hat{y})\\\hat{y}&=C_0\hat{z}\end{aligned} \tag{19}$$

With $L=\begin{bmatrix}l_1&l_2&\cdots&l_n\end{bmatrix}^T$ to be defined so that the eigenvalues of A_0+LC_0 are all negative and real.

By defining $e=z-\hat{z}$, the error dynamics can be written as:

$$\begin{aligned}\dot{e}&=(A_0+LC_0)e-\Delta\underline{a}y+\Delta B_0u\\e_1&=y-\tilde{y}=C_0e\end{aligned} \tag{20}$$

where Δa, and ΔB_0 are parameters uncertainties defined as normally distributed random variables with zero mean and known variance. Define p as,

$$\begin{aligned}p=[&\Delta a_1,\Delta a_2\dots,\Delta a_n,\Delta b_{0,0},\Delta b_{0,1}\dots,\\&\Delta b_{0,m-1},\Delta b_{1,0},\dots,\Delta b_{1,m-1},\dots,\Delta b_{n-1,m-1}]\in N(0,Q)\end{aligned} \tag{21}$$

where Q is the covariance matrix defined as

$$Q=E\{P_jP_k\}\ \forall j,k\ =\ (m+1)\times n \tag{22}$$

The solution of the differential equation for the error dynamics given by Eq. (20) is

$$\begin{aligned}e_1(t)=&C_0e^{(A_0+LC_0)t}e(0)+C_0\int_0^t e^{(A_0+LC_0)(t-\tau)}\sum_{i=1}^n E_i\Delta a_iy(\tau)\,d\tau\\&+C_0\int_0^t e^{(A_0+LC_0)(t-\tau)}\sum_{i=1}^n\sum_{j=0}^{m-1}E_i\Delta b_{i-1,j}u_j(\tau)\,d\tau\end{aligned} \tag{23}$$

where E_i have been introduced to write the solution in a compact for and are simply defined by

$$E_1=\begin{bmatrix}1&0&\cdots&0\end{bmatrix}^T,$$

$$E_i=\underbrace{\begin{bmatrix}0&\cdots&0&1&0&\cdots&0\end{bmatrix}^T}_{i^{th}\ position}$$

for i=2,...,n.

By switching the summations with the integral, we have

$$\begin{aligned}e_1(t)=&C_0e^{(A_0+LC_0)t}e(0)+\sum_{i=1}^n C_0\int_0^t e^{(A_0+LC_0)(t-\tau)}E_i\Delta a_iy(\tau)d\tau\\&+\sum_{i=1}^n\sum_{j=0}^{m-1}C_0\int_0^t e^{(A_0+LC_0)(t-\tau)}E_i\Delta b_{i-1,j}u_j(\tau)\,d\tau\end{aligned} \tag{24}$$

Since the parameters have zero mean, the expected value of Eq. (24) can be easily calculated

$$E\{e_1(t)\}=C_0e^{(A_0+LC_0)t}e(0)=\varepsilon_0 \tag{25}$$

that can be made vanish at any desired rated by an appropriate selection of the matrix L.

Considering auxiliary filters, that need to be found, for the threshold implementation, the last state n of these filters can be defined as

$$\xi_{i,n}=\int_0^t C_0e^{(A_0+LC_0)(t-\tau)}E_iy(\tau)d\tau \tag{26}$$

$$\psi_{ij,n}=\int_0^t C_0e^{(A_0+LC_0)(t-\tau)}E_iu_j(\tau)\,d\tau \tag{27}$$

Utilizing Eq. (22), (26) and (27), the variance of Eq. (24) can be easily written as

$$\begin{aligned}&Var\{e_1(t)\}=E\left\{(e_1-E(e_1))^2\right\}=\\&=E\left\{\left(\sum_{i=1}^n\Delta a_{i-1}\xi_{i,n}+\sum_{i=1}^n\sum_{j=0}^{m-1}\Delta b_{i-1,j}\psi_{ij,n}\right)^2\right\}\\&=\left[\xi_{1,n}\dots\xi_{n,n},\psi_{10,n}\dots\psi_{n\,m-1,n}\right]Q\left[\xi_{1,n}\dots\xi_{n,n},\psi_{10,n}\dots\psi_{n\,m-1,n}\right]^T\end{aligned} \tag{28}$$

If we define $\Theta^T=\left[\xi_{1,n}\dots\xi_{n,n},\psi_{10,n}\dots\psi_{n\,m-1,n}\right]$, according to Rayleigh-Ritz theorem, an upperbound of the variance can be obtained as

$$Var\{e_1(t)\}=\left|\Theta^T(t)Q\Theta(t)\right|\le\lambda_{\max}\|\Theta(t)\|_2^2=z_{th}(t) \tag{29}$$

with $\lambda_{\max}=\max\{eigenvalue(Q)\}$. This upperbound constitutes the adaptive threshold dynamics.

The state space representation of the adaptive threshold z_{th} in Eq. (29) can be obtained by observing that Eq. (26) and (27) are the outputs of linear filters described by the triplet $(A_0 + LC_0, E_i, C_0)$. Therefore, z_{th} can be implemented as follows

$$\begin{aligned}
&\dot{\xi}_i = (A_0 + LC_0)\xi_i + E_i y(t) \qquad i = 1,2,\ldots,n \\
&\xi_{i,n} = C_0 \xi_i \\
&\dot{\psi}_{ij} = (A_0 + LC_0)\psi_{ij} + E_i u_j(t) \\
&\psi_{ij,n} = C_0 \psi_{ij}, \quad i = 1,2,\ldots,n \qquad j = 0,1,2,\ldots,m-1 \\
&z_{th}(t) = \varepsilon_0 + \bar{\lambda}_{\max}\left(\sum_{i=1}^{n} \xi_{i,n}^2 + \sum_{j=0}^{m-1} \psi_{ij,n}^2\right)
\end{aligned} \tag{30}$$

where $\xi_i \in \mathbb{R}^n, \psi_{ij} \in \mathbb{R}^n, \forall i = 1...n,\ j = 0...m-1$ are the states of the auxiliary filters mentioned before with $\xi_{i,n}$ and $\psi_{ij,n}$ satisfying Eq. (26) and Eq. (27) respectively, $\xi_i(0) = 0$, $\psi_{ij}(0) = 0$, and $\bar{\lambda}_{\max}$ an upperbound of $\lambda_{\max}$.

In this case a fault is declared if $Var\{e_1(t)\} > z_{th}(t)$ which corresponds to signature S_1=1. The threshold just derived can be seen as $(m+1)$xn filters of order n. The high order of the threshold dynamics is the main drawback. The order can be further reduced to m+1 filters of order n by transforming the equations from observable form into controllable form, and combining the equations with the same input as shown in Eq. (31)

$$\begin{aligned}
&\dot{\gamma} = (A_0 + LC_0)^T \gamma + C_0^T y(t) \\
&\xi_{i,n} = E_i^T \gamma \\
&\dot{\psi}_j = (A_0 + LC_0)^T \psi_j + C_0^T u_j(t) \\
&\psi_{ij,n} = E_i^T \psi_j \quad i = 1\ldots n;\ j = 0\ldots m-1 \\
&Z_{th}(t) = \varepsilon_0 + \bar{\lambda}_{\max}\left(\sum_{i=1}^{n}\left(\xi_{i,n}\right)^2 + \sum_{j=0}^{m-1}\left(\psi_{ij,n}\right)^2\right)
\end{aligned} \tag{31}$$

where $\gamma \in \mathbb{R}^n, \psi_j \in \mathbb{R}^n$.

As mentioned before, the signature S_1 is obtained by comparing the adaptive threshold with the variance of the residual e_1. The variance of residual e_1 is here estimated by means of a recursive standard deviation algorithm described by

$$\begin{aligned}
(STD_{k+1})^2 &= \sum_{i=k+2-N}^{k+1} \frac{(e_{1,i} - \mu_i)^2}{N-1} \\
&= (STD_k)^2 + \frac{(e_{1,k+1} - \mu_{k+1})^2}{N-1} - \frac{(e_{1,k+1-N} - \mu_{k+1-N})^2}{N-1}
\end{aligned} \tag{32}$$

$$\mu_k = \sum_{i=k+1-N}^{k} \frac{e_{1,i}}{N} = \mu_{k-1} + \frac{e_{1,k}}{N} - \frac{e_{1,k-N}}{N} \tag{33}$$

where μ_k is the mean value of the residual and N is the moving window. Here a 1s moving window which contains 10,000 sampling points was considered for the implementation of the standard deviation (STD) algorithm.

Note that, as mentioned in section 2, parameter distributions and the corresponding covariance matrix can be pre-calculated for different classes of driving conditions (city, highway, etc.). An upperbound $\bar{\lambda}_{\max}$ can then be evaluated in each case and stored on board of the vehicle. A pattern recognition algorithm, like the one presented by Bo and Rizzoni (2006), can then be used to determine the current driving conditions and select the appropriate value of $\bar{\lambda}_{\max}$.

7. SIMULATION RESULTS

In order to test the effectiveness of the proposed diagnosis scheme, a system simulator was developed and the three different faults were injected into the system. The simulation time considered was 72s during which a portion of the Federal Urban Driving Schedule, Fig.4, was used to simulate the urban driving condition of the actual driving. Each fault is injected separately after 10s into the system. The belt slip and the voltage regulator faults are modeled as additive faults. The belt slip fault amount is 0.4 of the engine speed, and the voltage regulator is 0.3 of the nominal value of the voltage regulator. The residual along with thresholds plots are presented here. These plots show the effectiveness of the proposed fault diagnosis scheme in detecting and isolating the faults. This approach is capable in detecting the voltage regulator fault as it occurs whereas the belt slipping fault and open diode fault are detected at time 30s. That is when the input current takes effect combined with the change in speed. However, due to characteristics of the particular alternator chosen for this simulation, the movement of the threshold is limited. For S_2 signature, fixed thresholds at 13000, and -13000 are chosen as shown in Fig.8, Fig.10, and Fig.12. Figures 6, 7, 9 and 11 show the simulation results utilizing Gaussian distributed parameters threshold in order to obtain S_1 signature for the urban driving cycle. As it can be seen, this type of threshold is capable of detecting the fault when they occur specially in the case of voltage regulator fault. For the diode and belt slip fault, the detection occurs corresponding to a change of current load (Fig. 5).

One final note, this scheme can detect the belt slipping fault with fault amount as low as 30% with respect to the nominal value of the electrical frequency. Voltage regulator fault can be detected as low as 11% with respect to the nominal value of the voltage reference.

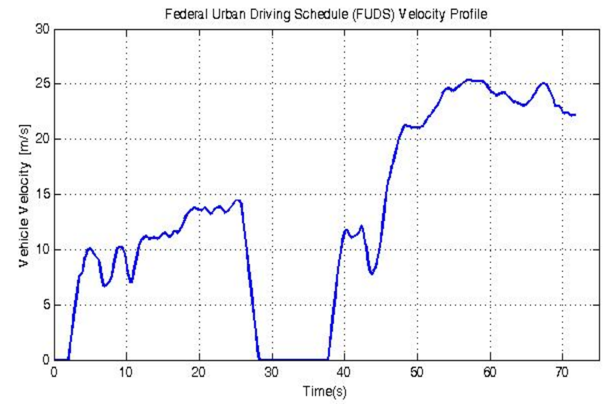

Figure 4. Federal Urban Driving Schedule.

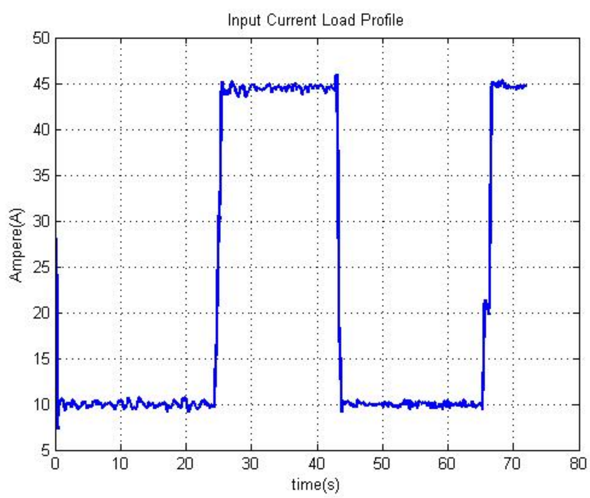

Figure 5. Current load profile.

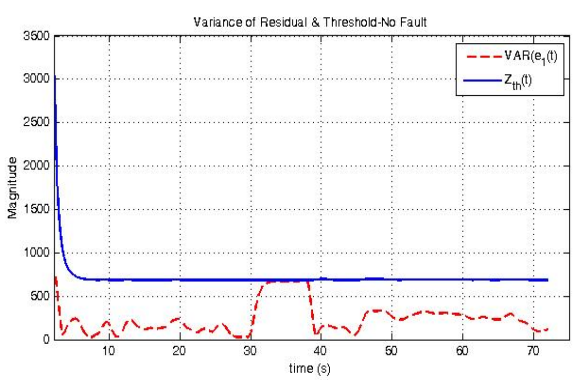

Figure 6. Residual of S_1 signal when no fault is injected.

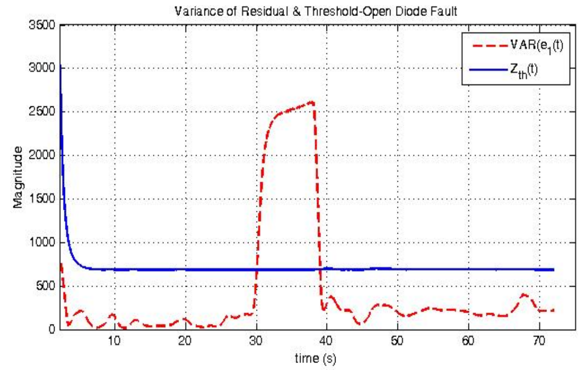

Figure 7. Residual of S_1 signal for open diode fault.

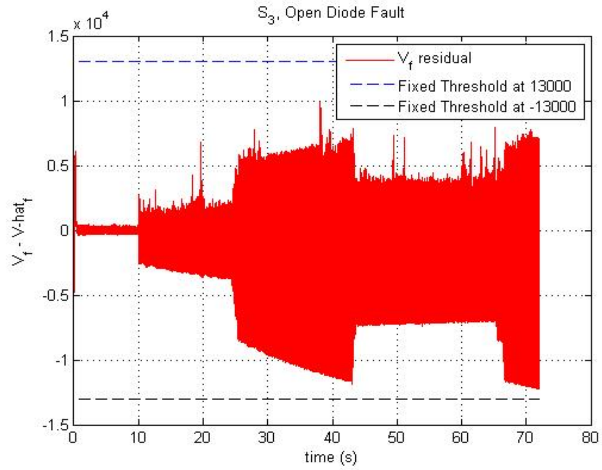

Figure 8. Residual of S_2 signal for open diode fault.

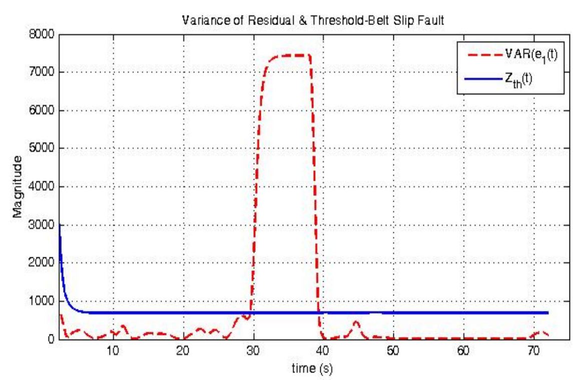

Figure 9. Residual of S_1 signal for belt slip fault.

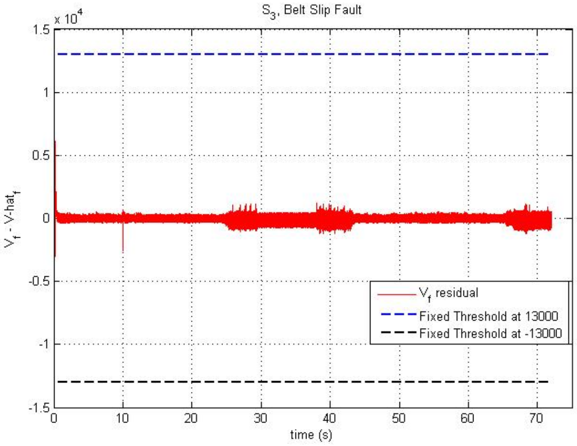

Figure 10. S_2 residual when belt slip fault is injected.

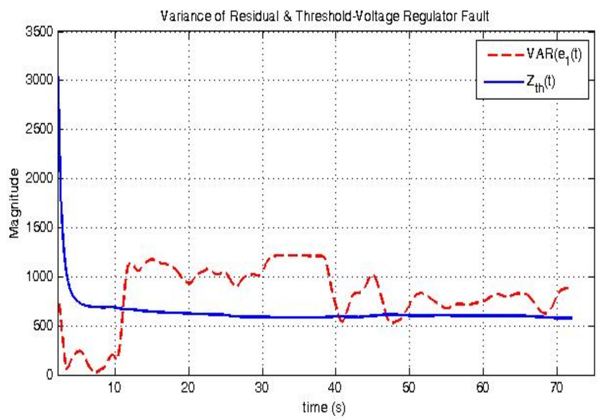

Figure 11. S_1 residual with voltage regulator fault.

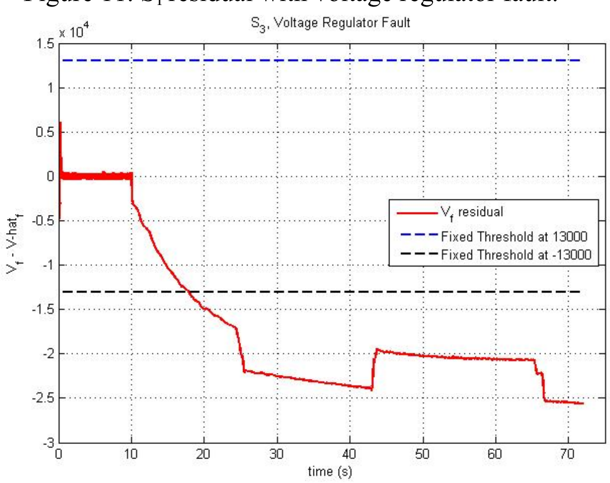

Figure 12. S_2 residual with voltage regulator fault.

8. CONCLUSION

This paper demonstrates the utilization of an adaptive threshold approach in designing a fault diagnosis scheme for the alternator subsystem in the EPGS system. An equivalent DC generator model was used in obtaining the observer-based adaptive threshold for the fault diagnosis scheme. Simulation results show that the proposed fault diagnosis scheme is effective in detecting and identifying the faults occurring in the alternator. Furthermore, the Gaussian distributed parameters adaptive threshold shows its effectiveness in detecting the faults occurring in the system and obtaining S_1 error signature.

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Ali Hashemi was born in Tehran, Iran in 1984. He is currently a masters student in Mechanical Engineering at Clemson University.

Pierluigi Pisu was born in Genoa, Italy in 1971. He received his Ph.D. in Electrical Engineering from the Ohio State University (Columbus, Ohio, USA) in 2002. In 2004, he was granted two US patents in area of model-based fault detection and isolation. He is currently Assistant Professor at the Department of Automotive Engineering at Clemson University. His research interests are in the area of fault diagnosis with application to vehicle systems, and energy management control of hybrid electric vehicles; he also worked in the area of sliding mode control and robust control. He is member of the ASME and SAE, and a recipient of the 2000 Outstanding Ph.D. Student Award by the Ohio State University Chapter of the Honor Society of Phi Kappa Phi.