Immune Systems Inspired Approach to Anomaly Detection, Fault Localization and Diagnosis in Complex Dynamic Systems

Dragan Djurdjanovic
University of Texas
1 University Station #C2200
Austin, TX 78712
dragand@me.utexas.edu

Clay Hearn
University of Texas
1 University Station #R7000
Austin, TX 78712
hearn@cem.utexas.edu

Yi Liu
University of Texas
1 University Station #C2200
Austin, TX 78712
Liuyi2009@mail.utexas.edu

Keywords: Immunity functions in engineering systems, precedent free isolation of faults, "divide and conquer" modeling of dynamic systems

Abstract

Almost prevalent use of electronics, complicated software, new materials, and technologies makes fault diagnosis and management in contemporary engineering systems increasingly difficult to deal with. Unavoidable design defects, quality variations in the production process, as well as different usage patterns, make it infeasible to foresee all possible faults that may occur on a given system. As a result, traditional precedent-based diagnostic approaches offer a very limited diagnostic coverage based on testing only for the *a priori* known or anticipated failures, often falsely presuming that the system is operating normally if the full set of diagnostic tests pass. To circumvent these difficulties and provide a more complete coverage for detection and localization of the source of any fault, a new paradigm for design of diagnostic systems is needed. An approach inspired by the functionalities and characteristics of natural immune systems is presented and discussed here. The capability of the newly proposed paradigm to isolate the source of an anomaly without the need to train with signatures characterizing the underlying fault is demonstrated in the simulations of a diesel engine Exhaust Gas Recirculation (EGR) system and a generator portion of a commercially available marine diesel-generator system.

1. INTRODUCTION

The immune system of a living organism serves the purpose of defending the organism from external intrusions, such as microbes, viruses, or foreign bodies. Natural immune systems accomplish anomaly detection, identification, and isolation of the root cause of anomalous behavior, as well as elimination of the problem. Improper function or failure of the immune system causes serious problems in the organism and often, its death. (Illnesses such as leukemia, cancer and AIDS manifest themselves through failures of the immune system to perform its functions).

In human society, thousands of years of evolution and the development of civilization are marked by dramatic improvements in tools and products. Breakthrough inventions and iterative design improvements result in products that have more power, deliver more functionality, and are easier to manufacture and use, etc. This process can be seen as being analogous to the process of natural evolution, in which living organisms have passed through series of "design iterations" in whom the strongest, most adaptive, and most functional have progressed to yield even more powerful and functional natural designs.

In parallel, engineering designs have been equipped with increasingly sophisticated capabilities for system performance, diagnosis, and prediction, especially in the case of sophisticated, expensive, and safety-critical systems, such as manufacturing equipment [1]-[3], computer networks [4][5], automotive systems [6][7], and chemical plants [8][9], etc. The purpose of these capabilities is to ensure proper functionality of the system and they can be seen as analogous to the immune system in a living organism.

Nevertheless, the way current diagnostic and prognostic capabilities are realized is significantly different from the way immune systems in living organisms are realized. Condition monitoring systems are based on sophisticated feature extraction, performance assessment, and condition diagnosis algorithms that are centered around recognizing indications of various abnormal behavior modes, which *a priori* have been known to exist and for which a behavior can be obtained from prior knowledge or training data. Recognition of those indications leads to natural identification of the underlying condition and an appropriate action to mitigate that abnormal condition. In a way, this approach to realizing the fault diagnosis and mitigation essentially represents part of the system design process, where the condition monitoring (just like the system itself) is carefully designed through selection of hardware and algorithms that facilitate maximum diagnostic coverage of the abnormal behavior modes that are *a priori* known to exist.

In the case of highly sophisticated and dynamic systems, such as automotive or aircraft engines, electrical generation systems, and others, the aforementioned approach to fault diagnosis and mitigation becomes excessively cumbersome because of the need to train the condition monitoring processes to recognize a large number of faults, some of which often cannot be anticipated in advance. Even for the cases one *is* able to anticipate in advance, many faults manifest themselves very differently under different control inputs, external loads, and environmental conditions, which makes training of diagnostic units for all possible conditions and all possible faults practically impossible.

This paper outlines results of the on-going research facilitating immunity-like reactions in complex systems of interacting dynamic subsystems. These reactions, similar to the mechanisms used by a human body to deal with newly encountered viruses, enable the system to detect and isolate the sources of previously unobserved faults ("precedent-free").

2. IMMUNE SYSTEM FUNCTIONALITIES IN COMPLEX DYNAMIC SYSTEMS

Anomaly detection can be formally described as identification of anomalous system behavior. Anomaly detection is one of the most important functionalities of a natural immune system. Before taking any actions to eliminate the foreign invaders, the immune system first has to discriminate between itself and harmful non-self. Natural immune systems are able to detect the/a harmful non-self even when the virus or bacteria has never been encountered. This capability of being able to identify the harmful non-self is vital for the survival of living organisms since infections are very diverse and unpredictable.

A natural immune system is also able to learn the protein structures of pathogens it encounters and retain memory of the structures so that future responses to the same pathogens are faster and more efficient [4]. This self-learning capability is important for natural immune systems to quickly adapt to new environments. As a result, each individual immune system is unique. Furthermore, the memorized pathogen structures enable natural immune systems to correctly identify the type of pathogens (analogous to fault identification) and later take appropriate actions.

Once the pathogens are detected and possibly identified, a natural immune system will have to eliminate them. Different pathogens are eliminated in different ways [4]. For pathogens that have never been encountered before, the initial response of a natural immune system is mild and it may take several weeks to eliminate the infection. During this process, the immune system is able to learn the protein structures of the newly encounter pathogens. On the other hand, if the pathogens have been encountered before or are similar to those encountered before, the response of the natural immune system is usually so efficient that there are no clinical indications of a re-infection.

Anomaly detection and localization, fault identification, and self-healing are essential for the survival of the living organism. The functionalities of immune systems are accomplished with the desired characteristics of autonomy, robustness, and uniqueness [4][10]. Autonomy of immune systems in living creatures displays itself in the ability to monitor and protect the living organism without outside control. The same mechanisms that monitor and protect the rest of the body also monitor and protect the immune system itself. Furthermore, the highly decentralized and distributed nature of an immune system and its ability to dynamically adapt to new situations constitute its robustness. Finally, the very adaptations that give an immune system its robustness render each individual immune system its unique characteristics. Namely, Since the immune system adapts to the intrusions, in spite of inherent similarities between individuals of the same species (individual machines of the same design), living (operating) conditions of each individual dictate the character of the immune system that the individual carries.

Inspired by the analogy between the functions of the natural immune system of living organisms and diagnostic systems in engineering, recent research proposed a novel approach to fault diagnosis and mitigation through anomaly detection, fault localization, fault diagnosis and performance recovery [11].

An anomaly ("intrusion") in system performance is first identified as a statistically significant departure of system behavior away from that described by the model of normal system behavior. Subsequently, if an anomaly is found, multiple anomaly detectors connecting to relevant subsystems of the anomalous system are generated, with each detector of the anomalous behavior splitting even further into detectors monitoring subsystems with increased granularity. Such multiplication of anomaly detectors ultimately leads to localization of anomalous subsystems within the system, even if the underlying fault was not observed before, as shown in [11][12][13]. Generation of additional anomaly detectors as an anomaly is detected mimics the way carriers of immunity are multiplied and flock around the intruders when an intrusion or illness is detected in a living organism [14].

Anomaly detection and localization are followed by fault diagnosis accomplished by matching the input-output patterns of the anomalous subsystem with the models of various previously seen faults. Each time the observed patterns could not be matched with any of the existing models, a new model needs to be created in order to recognize that particular situation in the future. This function is analogous to the process of generation of protein structures that match those of the intruding virus, after which antibodies with those protein structures can be synthesized to neutralize the virus [14].

Finally, based on the dynamic models identified through the diagnostic process, a control mechanism can be created to augment the nominal controllers in the system and restore as much as possible the original system function in the presence of a fault. This step resembles the generation of antibodies that neutralize the intruding virus and thus heal the organism.

3. GROWING STRUCTURE MULTIPLE MODEL SYSTEMS BASED ANOMALY DETECTION AND ISOLATION

Anomaly detection essentially boils down to detecting an abnormality in normal system operation. Identifying harmful non-self and quantifying the dissimilarity require an accurate definition of normal behavior. Therefore, constructing a profile representing normal behavior is essential for the success of the anomaly detection system. However, high complexity of the process dynamics of certain processes, such as the combustion process in an internal combustion engine, often prevents one from building an accurate model based on first principle. On the other hand, the process related signals are rather easy to obtain from sensors and embedded controllers. Consequently, data-driven approaches have been extensively employed in practice for modeling complex dynamic systems. Among those techniques, neural networks, such as Multi-Layer Perceptron (MLP) networks [15], Radial Basis Function (RBF) networks [16], and Recurrent Neural Networks (RNNs) [17]-[19], are the most extensively applied techniques because of their universal functional approximating capabilities [15], particularly in the case of complex nonlinear systems. Unlike feed-forward networks such as RBF and MLP, which have limitations of identifying temporal relationships in a time series, RNNs take into account temporal dependencies through local or global internal feedback connections in the network, which enables a good approximation of a wide class of nonlinear dynamical systems [15]. However, gradient descent algorithms commonly used to train RNNs exhibit problems during training, such as having difficulty dealing with long-term temporal dependencies in a time series [17]. In addition, finding a suitable number of hidden neurons and an appropriate RNN structure remains a challenging problem.

Since the training data for neural networks are usually taken from the entire operation space, they can be viewed as a global dynamic modeling approach [20]. Unlike the global dynamic modeling approach, an alternative for modeling nonlinear dynamic systems is the "divide and conquer" approach [21] which is based on the idea of dividing the whole system operation space into small sub-regions and modeling the local dynamics individually within each sub-region. The heuristics is that the modeling task for a small sub-region of the system behavior becomes easier to deal with than modeling the system as a whole. By dividing the operation space into small regions, the multiple local model approach can provide additional transparency about the physical processes, which is usually not easy to obtain for most of the global modeling approaches. This additional transparency would be beneficial for later controller reconfiguration.

Once an accurate model is obtained, the discrepancies between outputs of the model and the actual system can be utilized to detect and quantify the deviations. Since performance deviations are often caused by gradual component wear which may undergo a long developing process, quantification of anomaly severity is highly desirable for a number of applications, such as prognostics and health management systems (PHM) in aerospace industries [22][23], rotating machinery remaining life estimation [2][3] and condition-based maintenance (CBM) [24].

The recently introduced concept of Growing Structure Multiple Model System (GSMMS) [12] represents the latest development in the area of "divide and conquer" dynamic models. It uses the concept of a growing Self-Organizing Network (SON) [25] to partition the input space into regions of "similar" modeling behavior, within which relatively simpler dynamic models can be postulated. With minimal assumptions, the Growing SON concept uses unsupervised clustering to allow the input space partition to grow to an appropriate size, while simultaneously determining the shape and position of each local modeling region.

In the existing work, simple linear models are fit to the data within each local region, which boils this modeling approach down to essentially tiling of a highly curved surface with an appropriate number of flat tiles. Highly curved areas require high number of smaller tiles, while large, flat areas require fewer tiles of larger size. The size, position, and shape of each tile are determined through the growth and adaptation of the SON. The motion of SON nodes pushes their regions of validity towards areas of high curvature (high nonlinearity), thus enabling finer partition of state space areas with higher nonlinearity. Following the well-known heuristics of unsupervised clustering, SON node motion (and hence the motion of the corresponding local models) is more pronounced closer to the training item, thus facilitating local adaptations of the model system.

The problem of the size of the GSMMS is solved through a novel growth mechanism, where new nodes (new local models) are added to the system between the two worst local models in the GSMMS (two models with highest modeling errors). This essentially results in the addition of more "tiles" to the areas where modeling errors are high, i.e., to the areas where system nonlinearity is high.

Anomaly detection based on GSMMS modeling is realized through comparison of the statistical characteristics of the GSMMS modeling residuals during normal behavior with statistical properties of the most recently observed residuals. Since any GSMMS model inherently has regions with different levels of accuracy, error characteristics are statistically tracked separately inside each region by setting up standard Statistical Process Control (SPC) charts inside each region.

Another possible concept that can be employed to track system performance based on the GSMMS residuals is the concept of regional Confidence Values (CVs) used in [13]. A regional CV describes the overlap area between the probability density function of the modeling residuals displayed during the normal behavior and the PDF of the residuals corresponding to the current (possibly faulty) behavior. The regional CVs are merged into a global CV defined as the geometric mean to simplify the monitoring scheme [13]. CVs close to 1 indicate high level of similarity and hence nearly normal system behavior. Lower values of CVs indicate low similarity with the normal behavior and hence possible presence of a fault (lowest theoretical value for a CV is zero). Figure 1 illustrates the concept of a CV.

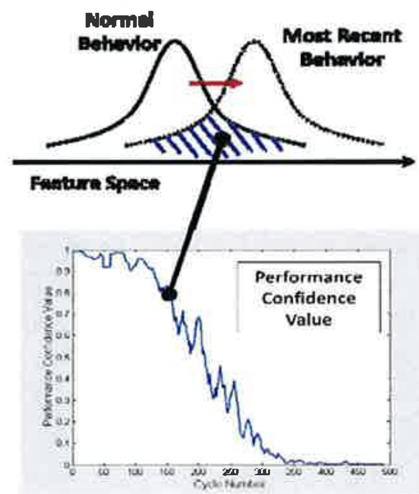


Figure 1. Concept of performance Confidence Values (CVs). The bottom plot illustrates CVs obtained from spindle load signals, characterizing wearout of a boring tool in an automotive plant

Once an anomaly is detected, the source of anomalous behavior can be isolated using distributed anomaly detection. Essentially, the anomaly detector can split into a set of anomaly detectors monitoring relevant subsystems, each of which can further decompose if it detects an anomaly. Repetition of this process leads to detection of anomalies in systems of increased granularity and subsequent isolation of anomalous subsystems, without the need for training signals corresponding to the abnormal system behavior (precedent-free).

4. ANOMALY DETECTION AND ISOLATION IN A DIESEL ENGINE EXHAUST GAS RECIRCULATION (EGR) SYSTEM

Let us illustrate this concept with the example of fault isolation in an EGR valve system taken from [13]. EGR systems are widely utilized in diesel engines to reduce NOx emission and improve fuel efficiency. Figure 2 shows the block diagram of an EGR valve system, while Figure 3 shows connections of the anomaly detector monitoring the EGR valve system. Figure 4(a) characterizes three various faults inserted into the EGR valve at time t = 1500 s, while Figure 4(b) shows corresponding performance CVs. All results are obtained using high-fidelity simulations of a diesel engine [26]. It is obvious that all three faults are successfully identified through the drop of the performance CVs. In addition, a more severe drop of CVs characterizes more severe faults. The next step is to isolate the source of the fault, which in this case is the EGR valve body.

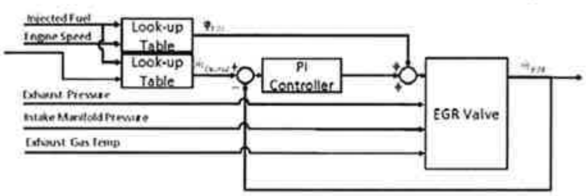


Figure 2. Block Diagram of The EGR Valve System

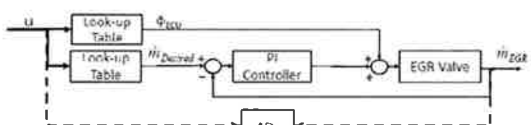


Figure 3. Block Diagram of anomaly detector (AD_1) monitoring the entire EGR valve system

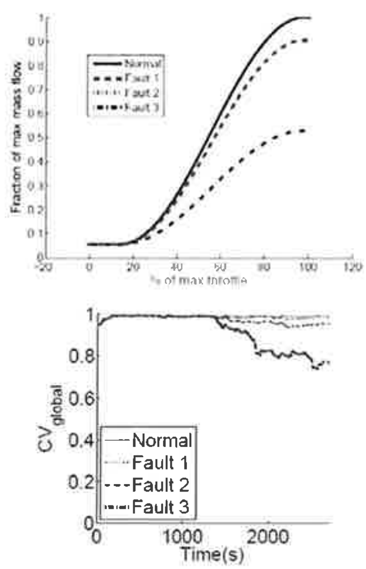


Figure 4. Results of anomaly detection in the EGR valve system. The top plot gives characteristic curves for various anomalies inserted at time t = 1500 s into the EGR valve, while the bottom plot gives performance CVs for the three anomalies illustrated in plot (a).

If the anomaly detector AD_1 detects an anomaly ("non-self"), it splits into four anomaly detectors monitoring the relevant subsystems, as illustrated in Figure 5. Figure 6 shows results of individual subsystem anomaly detectors once anomalies illustrated in Figure 4 are introduced. Interpretation of results of distributed anomaly detection shown in Figure 6 naturally leads to the faulty subsystem. Figures 6(a) and 6(b) show the performance CVs output by the anomaly detectors monitoring the two lookup tables in the system, Figure 6(c) shows performance CVs originating from the anomaly detector monitoring the PI controller performance and Figure 6(d) shows CVs output by the anomaly detector monitoring the EGR valve. The only CV plot showing significant drops is the one shown in plot (d), indicating that the anomaly originated from the EGR valve (which truly was the case). Thus, we are able to localize the source of anomalous behavior *without ever training classifiers to recognize those particular faults.*

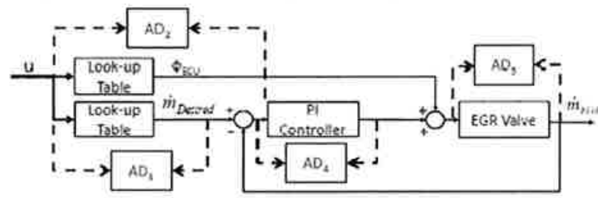
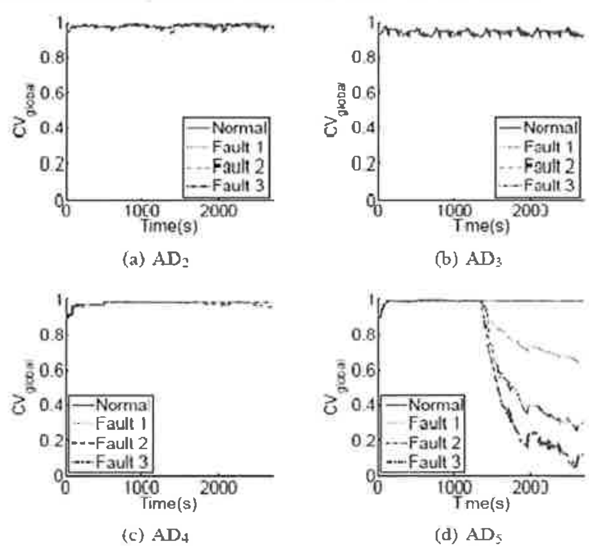


Figure 5. Block diagram of Distributed Anomaly Detection that occurs when AD_1 detects presence of an anomaly in the EGR valve system



(a) AD_2 (b) AD_3

(c) AD_4 (d) AD_5

Figure 6. Performance CVs output by anomaly detectors AD_2-AD_5 (illustrated in Figure 5) when various faults were inserted into the valve body. Clearly, only AD_5 indicates the presence of a fault, thus localizing the source of the anomaly to the valve body.

Similarly, Figure 7 shows the CVs output by AD_1 when various delays were inserted into the PI-controller signals, while Figure 8 shows CVs output by the anomaly detectors AD_2-AD_5 illustrated in Figure 5. It is clear that only AD_4 shows abnormally low values and hence, we can conclude that the PI controller is the source of the anomaly (once again, no signals emanated by the faulty system were used whatsoever).

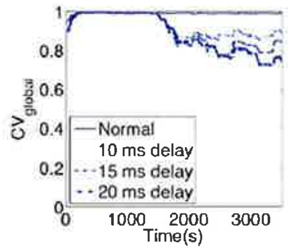


Figure 7. Performance CVs output by the anomaly detector AD_1 (illustrated in Figure 3) when various delays were inserted into the PI controller signal

5. ANOMALY DETECTION AND ISOLATION IN AN ALTERNATING CURRENT (AC) GENERATOR SYSTEM

The concept of precedent-free fault isolation through distributed anomaly detection was also implemented on the alternating current (AC) generator system. A numerical model was developed in Simulink® [27] to simulate the operational characteristics of the generator portion of a commercially available marine diesel-generator. This model is comprised of multiple interacting nonlinear sub-systems, which provided the training data for the subsequent GSMMS based anomaly detection and isolation. The generator system consists of two major subsystems – the main generator which provides the three-phase AC voltage output for downstream loads, and an exciter which provides the voltage to the main generator field winding through diode bridge rectification. The three-phase voltage output is controlled through a voltage regulator that supplies power to the field winding of the exciter. The voltage regulator is powered by a separate permanent magnet generator (PMG), which is not considered in our model at this time. Figure 9 illustrates the generator portion modeled in this paper.

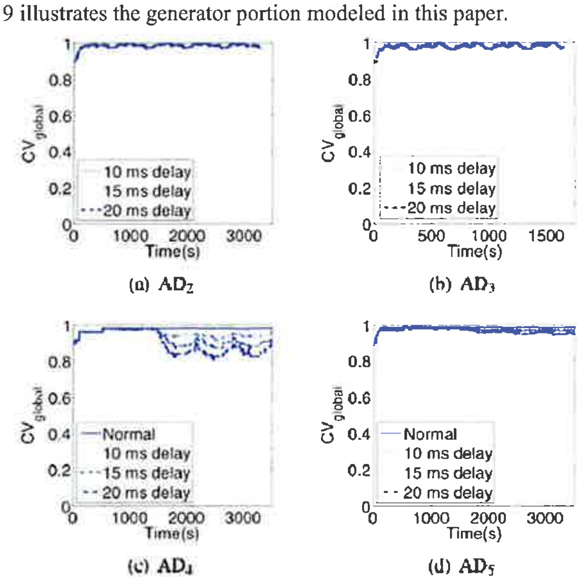


Figure 8. Performance CVs output by anomaly detectors AD_2-AD_5 (illustrated in Figure 5) when various delays were inserted into the PI controller signals. Clearly, only AD_4 indicates the presence of a fault, thus localizing the source of the anomaly to the PI controller.

The main generator and exciter can both be modeled through a dq0 transformation of the three-phase AC voltages and currents [28]. The dq0 transformation is standard technique for modeling AC machines which provide a set of equations with time-invariant coefficients. The resulting state space model of the generator was expressed as

$$\dot{\lambda}_q = \frac{r_s(L_{MQ} - L_{ls})}{L_{ls}^2}\lambda_q - \frac{P}{2}\omega_{rm}\lambda_d + \frac{r_s L_{MQ}}{L_{ls}L'_{lkq}}\lambda'_{kq} + v_q \tag{1}$$

$$\dot{\lambda}_d = \frac{P}{2}\omega_{rm}\lambda_q + \frac{r_s(L_{MD} - L_{ls})}{L_{ls}^2}\lambda_d + \frac{r_s L_{MD}}{L_{ls}L'_{lkd}}\lambda'_{kd} + \frac{r_s L_{MD}}{L_{ls}L'_{lf}}\lambda'_f + v_d \tag{2}$$

$$\dot{\lambda}_0 = v_0 - \frac{r_s}{L_{ls}}\lambda_0 \tag{3}$$

$$\dot{\lambda}'_{kq} = \frac{r'_{kq}L_{MQ}}{L_{ls}L'_{lkq}}\lambda_q + \frac{r'_{kq}(L_{MQ} - L'_{lkq})}{L'^2_{lkq}}\lambda'_{kq} \tag{4}$$

$$\dot{\lambda}'_{kd} = \frac{r'_{kd}L_{MD}}{L_{ls}L'_{lkd}}\lambda_d + \frac{r'_{kd}(L_{MD} - L'_{lkd})}{L'^2_{lkd}}\lambda'_{kd} + \frac{r'_{kd}L_{MD}}{L'_{lf}L'_{lkd}}\lambda'_f \tag{5}$$

$$\dot{\lambda}'_f = \frac{r'_f L_{MD}}{L_{ls}L'_{lf}}\lambda_d + \frac{r'_f L_{MD}}{L'_{lkd}L'_{lf}}\lambda'_{kd} + \frac{r'_f(L_{MD} - L'_{lf})}{L'^2_{lf}}\lambda'_f + v'_f \tag{6}$$

$$\dot{\omega}_{rm} = \frac{3P(L_{MD} - L_{MQ})\lambda_q}{4JL_{ls}^2}\lambda_d - \frac{3PL_{MQ}\lambda_d}{4JL_{ls}L'_{lkq}}\lambda'_{kq} + \frac{3PL_{MD}\lambda_q}{4JL_{ls}L'_{lkd}}\lambda'_{kd} + \frac{3PL_{MD}\lambda_q}{4JL_{ls}L'_{lf}}\lambda'_f - \frac{B_m}{J}\omega_{rm} + \frac{\tau_{mech}}{J} \tag{7}$$

Where $\dot{\lambda}_q$, $\dot{\lambda}_d$, and $\dot{\lambda}_0$ are the q-axis, d-axis, 0-axis flux linkages, respectively; λ'_{kq} and λ'_{kd} are the q-axis and d-axis dampening winding flux linkages, respectively; λ'_f is the field axis dampening winding flux linkage; ω_{rm} is the mechanical rotor speed; P is the number of pole pairs; r_s is the stator winding resistance; r'_{kq} and r'_{kd} are the q-axis and d-axis damper winding resistances, respectively; L_{MQ} and L_{MD} are the equivalent q-axis and d-axis magnetizing inductances, respectively; L_{ls} is the leakage inductance; L'_{lkq} and L'_{lkd} are the q-axis and d-axis damper winding inductances, respectively; L'_{lf} is the field inductance; J is the rotor inertia; and B_m is the mechanical dampening. The main generator model utilizes all seven states represented in equations (1)-(7), whereas the exciter model does not include equations (4) and (5), representing the flux linkages of the q and d axis damper windings, and .

Model parameters for the main generator were obtained from the manufacturer of the generator, while the exciter parameters were estimated by the size requirements to power the main field windings. Estimates of time constants and reactances for the synchronous machines were obtained from [29].

Additional nonlinearities are induced by the field rectification circuit, modeled using the SimPower system toolbox in Simulink®. The rectifier provides DC excitation of the main field from the AC exciter input. The on-off switching actions of the diodes induce harmonics into the system which further increases modeling complexity.

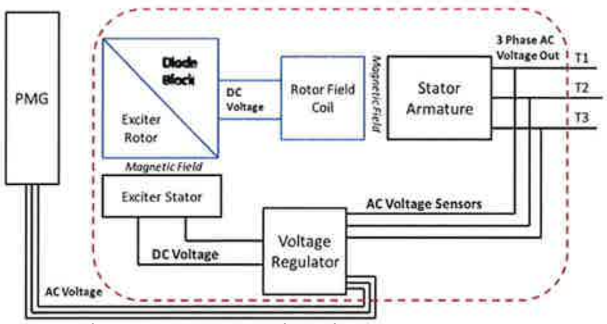


Figure 9. Generator component schematic

The speed and voltage regulation are implemented by separate PI controllers that maintain a 1500 RPM shaft speed and 415 V_{ll} (line to line voltage). The torque developed by the speed regulator represents the diesel engine input torque for the full diesel-electric generator. A switchable load bank is incorporated into the Simulink® model to provide time varying load demands which excite the transient dynamics of the generator and provide a more realistic setting for our analysis. Figure 10 shows a typical power output observed in one of our data sets. Faults were inserted into the system by modifying model coefficients, such as generator dampening, or inducing ground faults into the system.

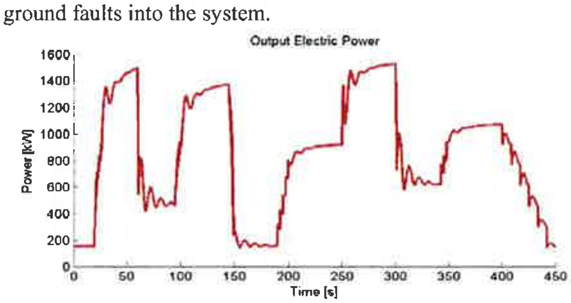


Figure 10. Example of a typical generator power output corresponding to variable load demands

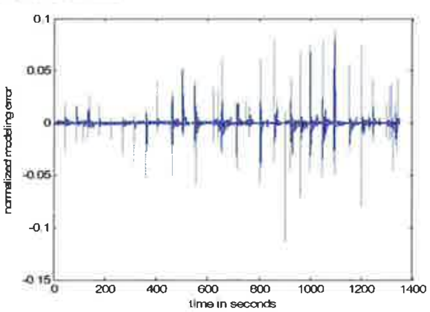


Figure 11. GSMMS residuals during normal system behavior

First, an overall anomaly detector for the whole generator system was constructed by building the GSMMS model of the system. Inputs into this model were the engine torque, exciter field voltage, main generator torque, exciter voltage (one phase only), and main generator voltage, while the output was the generator current. Data corresponding to three different external load profiles (each 450 s long) were used for training of the GSMMS and the corresponding anomaly detector, while the data corresponding to a previously unseen load profile were used for testing. The resulting GSMMS model had 20 first-order local linear models and inside each of the local regions of validity, a simple SPC chart was set up to monitor the GSMMS modeling errors.

Figure 11 shows GSMMS modeling errors during normal system operation. These errors show an obvious non-stationary pattern, which would traditionally lead numerous false alarms (a traditional anomaly detector would signal an anomaly each time modeling errors spike in their size). Figure 12 shows the corresponding modeling residuals inside 4 regions (out of 20) of the GSMMS model. It is obvious that errors inside these regions are stationary and do not signal any anomaly (control limits in all charts are indicating 3-sigma limits). Such behavior was visible in all 20 local regions.

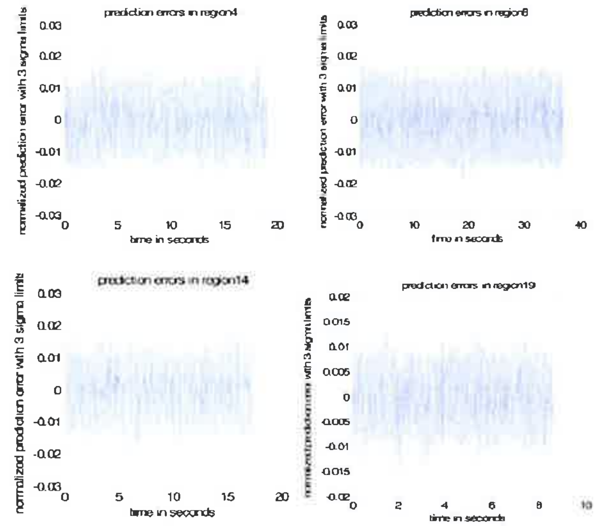


Figure 12. GSMMS residuals during normal system behavior, as observed in four different regions. All 20 regions indicated "in-control" modeling residuals (i.e., no anomaly was signaled).

On the other hand, when errors were introduced into the generator model by altering some of the model parameters, the regional GSMMS residuals clearly showed those faults. Figure 13 shows modeling residuals in two model regions when a grounding fault was inserted, while Figure 14 shows GSMMS residuals in two regions when the bearing friction in the model was increased. Results shown in Figures 11-14 clearly show that regional analysis of modeling residuals is highly beneficial for behavior characterization.

Once an anomaly in the generator was detected, the overall anomaly detector split into an anomaly detector corresponding to the exciter and an anomaly detector corresponding to the electromechanical portion of the generator, as illustrated in Figure 15.

Figure 16 shows the modeling residuals in two regions of the GSMMS corresponding to the exciter portion of the generator, as observed when a grounding fault was introduced. It was obvious that an anomaly is present in the exciter since SPC residual charts in all five GSMMS regions signaled a fault. In the same time, the GSMMS of the electromechanical portion of the system did not signal an anomaly. Similarly, Figure 15 shows residuals in two regions of the GSMMS model corresponding to the electro-mechanical portion of the generator when a friction fault was introduced. Clearly, the fault is present in this subsystem, as the total of five out of 20 regions signaled an abnormality. In the same time, the GSMMS of the exciter did not signal an anomaly.

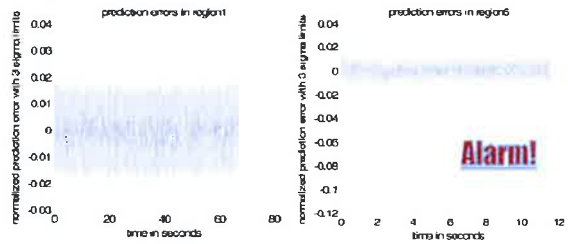


Figure 13. GSMMS residuals in two different regions, as observed when a grounding fault was introduced. Five (out of 20) regions signaled a fault, using the simple +/-3-sigma limit control charts of modeling residuals.

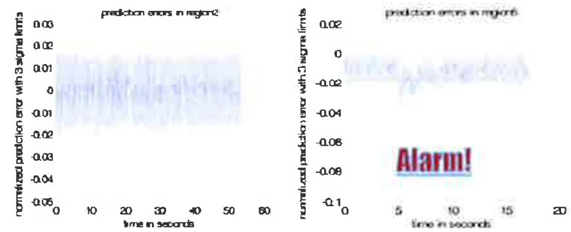


Figure 14. GSMMS residuals in two different regions, as observed when increased friction was inserted into the model. Six (out of 20) regions signaled a fault, using the simple +/-3-sigma limit control charts of modeling residuals.

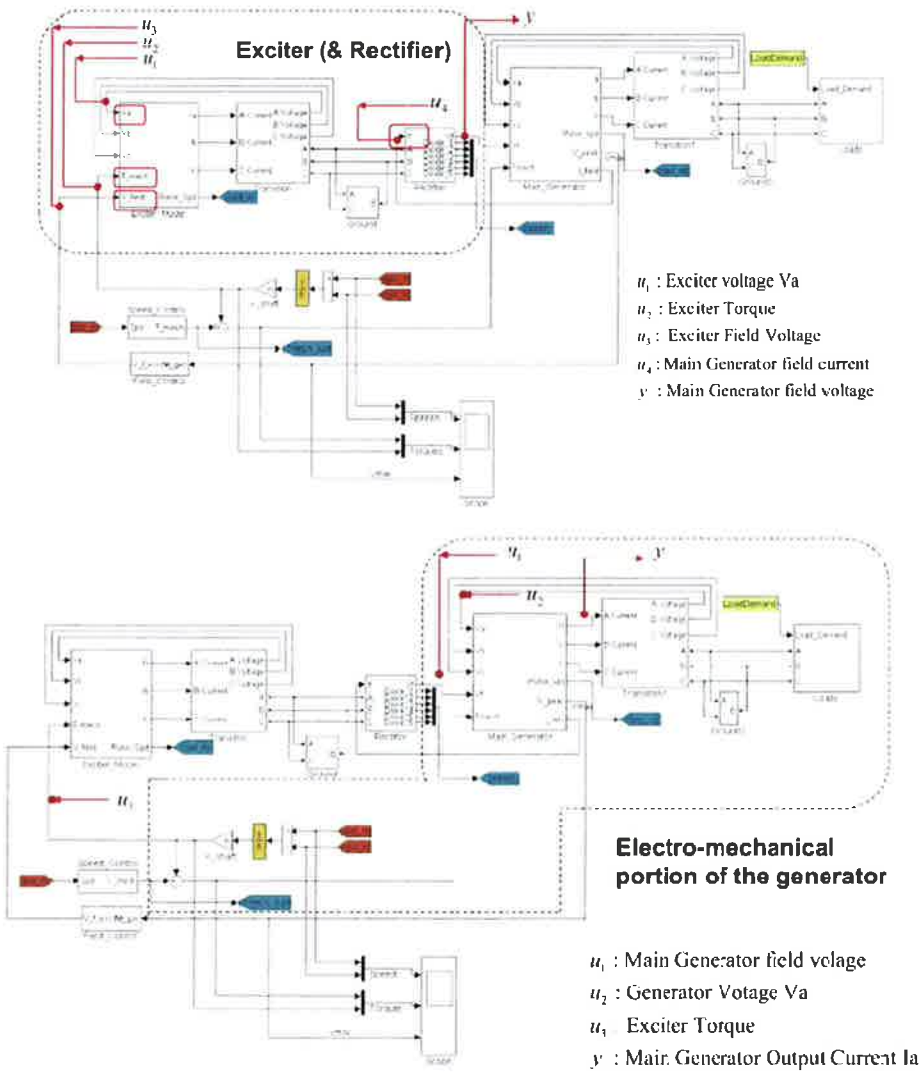


Figure 15. Schematics of the two anomaly detectors formed once the overall anomaly detector monitoring the entire generator system detects an anomaly.

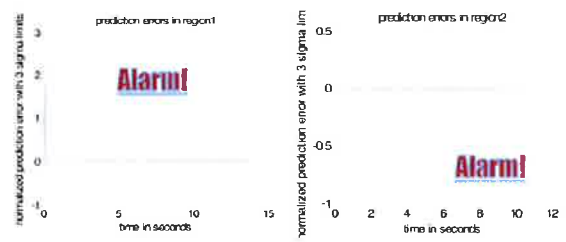


Figure 16. Residuals in two different regions of the GSMMS modeling the exciter subsystem, as observed when a grounding fault was inserted into the model. All five regions signaled a fault, using the simple +/-3-sigma limit control charts of modeling residuals.

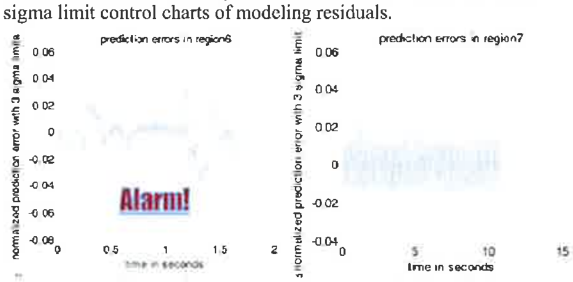


Figure 17. Residuals in two different regions of the GSMMS modeling the electromechanical portion of the generator, as observed when increased friction was simulated in the model. Five (out of 20) regions signaled a fault, using the simple +/- 3-sigma limit control charts of modeling residuals.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we described a novel method for anomaly detection, fault localization and diagnosis, inspired by the way these functions are accomplished in natural systems. Anomalies are detected as statistical departures from normal behavioral patterns and are localized to the culprit system(s) through distributed anomaly detection that delves into subsystems of deeper granularity each time an anomaly is detected. Fault diagnosis is accomplished through the traditional diagnostic approaches of matching model indications of known faults with signatures of the currently observed system behavior.

The key enabling method facilitating the above-mentioned vision are the newly developed generic approach to modeling of complex system dynamics, allowing anomaly detectors and diagnosers to use essentially the same modeling mechanism to successively connect to different inputs and outputs (corresponding to different subsystems), identify models of the corresponding subsystems, and accomplish anomaly detection and diagnosis. Examples of anomaly detection, fault localization and diagnosis in the diesel engine EGR valve system and marine generator system are presented.

Future research will be dedicated to utilizing local model tractability emanating from the "divide and conquer" modeling approaches to devise methods for controller adaptation that will facilitate performance recovery in the presence of faults. Ability to adaptively detect, localize, characterize, and compensate for faults will enable one to explore possibilities of artificially vaccinating systems against different faults by inserting those faults into a selected group of "test systems" that will develop immunity to those faults and whose "antibodies" could then be distributed into the entire fleet of corresponding systems as diagnostic and control software patches. We also believe that immune system inspiration can have far fetching influence in future developments in other engineering areas, such as manufacturing, aerospace, and biomedical systems.

REFERENCES

[1] Rao, B., 1996, "Handbook of Condition Monitoring," Elsevier Advanced Technology.

[2] Randall, R.B., 2004, "State of the art in monitoring rotating machinery – part 1," Sound & Vibr., 38, no. 3, (March): 14-21.

[3] Randall, R.B., 2004, "State of the art in monitoring rotating machinery – part 2," Sound & Vibr., 38, no. 5, (May): 10-17.

[4] Hofmeyr, S., and S. Forrest, 2000, "Architecture for an artificial immune system," Evolutionary Computation, 8, no. 4: 443-473.

[5] Denning, D., 1987, "An intrusion detection model," IEEE Trans. Software Eng., vol. SE-13, no. 2, (February): 222–232.

[6] Kim, Y.-W., G. Rizzoni, and V. Utkin, 1998, "Automotive engine diagnosis and control via nonlinear estimation," IEEE Control Sys. Magazine, 18, no. 5, (October): 84-99.

[7] Patton, R., P.M. Frank, and R.N. Clark. 1996. Issues of Fault Diagnosis for Dynamic Systems. New York, Springer Verlag.

[8] Venkatasubramanian, V., R. Rengaswamy, K. Yin, and S.N. Kavuri, 2003, "A review of process fault detection and diagnosis part I: Quantitative model-based methods," Comp. & Chem. Eng., 27, no. 3: 293-311.

[9] Venkatasubramanian, V., R. Rengaswamy, and S.N. Kavuri, 2003, "A review of process fault detection and diagnosis part II: Qualitative models and search strategies," Comp. & Chem. Eng., 27, no. 3: 313-326.

[10] Brotherton T., and T. Johnson, 2001, "Anomaly detection for advanced military aircraft using neural networks," 6: 3113-3123.

[11] D. Djurdjanovic, J. Liu, K.A. Marko and J. Ni, 2010, "Immune Systems Inspired Approach to Anomaly Detection, Fault Localization and Diagnosis in Automotive Engines," in *Applications of Neural Networks in High Assurance Systems* (edited by Y. Liu and J. Schumann), Springer, 141-164.

[12] Liu, J., D. Djurdjanovic, K.A. Marko and J. Ni, 2009, "Growing structure multiple model system for anomaly detection and fault diagnosis," Trans. of ASME, J. of Dyna. Sys., Measurements and Control, 131, no. 5: 051001-1-051001-13.

[13] Cholette, M. and D. Djurdjanovic, 2009, "Precedent-Free Fault Isolation in a Diesel Engine EGR Valve System", in Proc. of the 2009 ASME Dyn. Sys. and Control Conf. (DSCC), paper no. 2706.

[14] Forest, S. and C. Beauchemin, "Computer Immunology," Immunol. Rev., 216, no. 1: 176-197.

[15] Haykin, S.S. 1999. "Neural networks: a comprehensive foundation," 2nd ed. Upper Saddle River, N.J.: Prentice Hall.

[16] Cho, K.B. and B.H. Wang, 1996, "Radial basis function based adaptive fuzzy systems and their applications to system identification and prediction," Fuzzy Sets and Systems, 83, no. 3: 325-339.

[17] Han, M., J. Xi, S. Xu, and F.-L. Yin, 2004, "Prediction of chaotic time series based on the recurrent predictor neural network," IEEE Trans. Signal Processing, 52, no. 12: 3409-3416.

[18] Leung, H., T. Lo, and S. Wang, 2001, "Prediction of noisy chaotic time series using an optimal radial basis function neural network," IEEE Trans. Neural Networks, 12, no. 5: 1163-1172.

[19] Connor, J.T., R.D. Martin, and L. Atlas, 1994, "Recurrent neural networks and robust time series prediction," IEEE Trans. N. Networks, 5, no. 2: 240-253.

[20] Principe, J.C., L. Wang, and M.A. Motter, 1998, "Local dynamic modeling with self-organizing maps and applications to nonlinear system identification and control," Proc. IEEE, 86, no. 11: 2240-2258.

[21] Kim, S.-P., J.C. Sanchez, D. Erdogmus, Y.N. Rao, J. Wessberg, J.C. Principe, and M. Nicolelis, 2003, "Divide-and-conquer

approach for brain machine interfaces: Nonlinear mixture of competitive linear models," Neural Networks, 16, no. 5-6: 865-871.

[22] Roemer, M., E. Nwadiogbu, and G. Bloor, 2001, "Development of diagnostic and prognostic technologies for aerospace health management applications," Proc. IEEE Aerospace Conf., (Big Sky, MT, USA March 10-17), 6-3139-3147.

[23] Brotherton, T., P. Grabill, D. Wroblewski, R. Friend, B. Sotomayer, and J. Berry, 2002, "A testbed for data fusion for engine diagnostics and prognostics," Proc. IEEE Aerospace Conf., (Big Sky, MT, USA, March 9-16), 6-3042.

[24] Hosseini, M.M., R.M. Kerr, and R.B. Randall, 2000, "Inspection model with minimal and major maintenance for a system with deterioration and Poisson failures," IEEE Trans. Reliability, 49, no. 1: 88-98.

[25] Fritzke, B., 1994, "Growing cell structures - a self-organizing network for unsupervised and supervised learning," Neural Networks, 7, no. 9: 1441-1460.

[26] TESIS DYNAWARE, "en-DYNAR THERMOSR 2.0 Block Reference Manual" June 2006.

[27] MathWorks, http://www.mathrowks.com/producs/simulink/, 2010.

[28] Ong, Chee-Mun. 1998. Dynamic Simulation of Electric Machinery. Prentice Hall, Upper Saddle River, NJ.

[29] Sarama, Mulukutla S. 1994. Electric Machines; Steady State Theory and Dynamic Performance. 2nd Ed. West Publishing Company, Minneapolis/St. Paul.

7. BIOGRAPHY

Dragan Djurdjanovic obtained his BS in Mechanical Engineering and Applied Mathematics in 1997 from the University of Nis, Serbia, his MS in Mechanical Engineering from the Nanyang Technological University and his MS in Electrical Engineering and Ph.D. in Mechanical Engioneering in 2002 from the University of Michigan. He was a research faculty at the Dept. of Mechanical Engineering at the University of Michigan from 2003-2007 and since 2007 he is an Assistant Professor in the Dept. of Mechanical Engineering at the University of Texas at Austin.

Yi Liu obtained his BS in Electrical Engineering and Automation in 2001 from Beihang University, China and his MS in Mechanical Engineering from Southern Illinois University at Edwardsville in 2008. Since 2009, he is pursuing his Ph.D. in Mechanical Engineering from the University of Texas at Austin.

Clay Hearn obtained his BS and MS in Mechanical Engineering from the University of Texas at Austin in 2001 and 2008, respectively. He has been a Research Engineer at the Center for Electromechanics at the University of Texas at Austin since 2002 and is currently pursuing his Ph.D. in Mechanical Engineering at the University of Texas in Austin.