Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Artificial Immune Intelligent Maintenance System – Diagnostic Agents

Marcos Zuccolotto*, Luca Fasanotti,**
Sergio Cavalieri, Carlos Eduardo Pereira***

**Electrical Engineering Department, Federal University of Rio Grande do Sul*
Porto Alegre, Brasil (e-mail marcos.zuccolotto@ufrgs.br, cepereira@ece.ufrgs.br).
***CELS, Università degli studi di Bergamo*
Bergamo, Italy (e-mail luca.fasanotti@unibg.it, sergio.cavalieri@unibg.it)

Abstract: **The Artificial Immune Intelligent Maintenance System (AI2MS) is an architecture proposal for a Distributed Intelligent Maintenance System (IMS) using Artificial Immune Systems concepts. Equipment has its own embedded AIS, performing a local diagnosis. This proposal is modeled and implemented using multi-agent systems, where every autonomous IMS is mapped to a set of local agents, while the communication and decision process between IMSs are mapped to global agents. This paper describes the diagnostic agents implementation of the AI2MS and present some preliminary results deriving from the application of the proposed approach to a case study.**

Keywords: **Fault detection, fault diagnosis, distributed artificial intelligent, intelligent maintenance systems, artificial immune systems.**

1. INTRODUCTION

In today's highly globalized market, in which companies must have high productivity, high quality and low cost for their products and services, equipment maintenance has become a crucial factor to achieve these requirements, as pointed by (Lee et al. 2006), (Lu & Sy 2009) (Lee et al., 2006; Lu, Durocher, Stemper, 2009; Niu; Yang, 2010).

Even when equipment seems to fail abruptly, the degradation is a gradual process and can be measured. Based on that, there are increasingly more maintenance systems which based on degradation levels seek to predict failures, receiving names such "Intelligent Maintenance Systems" (IMS) (Lee et al., 2006). The goal of an IMS is to migrate from traditional systems to proactive ones, based on equipment state of operation and degradation.

The growing complexity of modern engineering systems and manufacturing process is an obstacle to concept and implement IMS and keep these systems operating at high levels of reliability. To face these challenge Lee et al. have introduced the idea of transforming the IMS to engineering immune systems (EIS) Artificial Immune Systems (AIS) are considered one of the right approach to get self-maintenance systems (Lee et al. 2011a)

An architecture for a Distributed IMS using Artificial Immune Systems (AIS) concepts, called AI2MS, was proposed by Zuccolotto,(Zuccolotto et al. 2013a). The main goal is to improve the overall performance of the IMS the adoption of online and offline mechanisms for information exchange and a continuous learning process.

This paper presents the first steps of the AI2MS design and implementation, with focus on the Device Layer Agents (Diagnostics Agents, Sensor Agent and Evolution Agent). Those agents represent the basic level of AI2MS. Early test points to a promise performance in fault coverage.

2. ARTIFICIAL IMMUNE SYSTEMS (AIS)

AIS are defined by Timmis as "Adaptive systems, inspired by theoretical immunology and observed immune functions, principles and models, which are applied to problem solving"(Timmis et al. 2008).

Immune system is the natural defense against foreign harmful substances and microorganisms (like virus or bacteria), called pathogens. Adaptive immune system is a more complex subsystem of immune system, capable to identify new threats, build a response to them and embody this knowledge(Somayaji et al. 1997)(Castro & Zuben 1999)(Aickelin & Dasgupta 2005).

AIS tries to reproduce strategies of the adaptive immune system to acquire it´s features, as distributability, adaptability, abnormality detection and disposability (Somayaji et al. 1997)(Dasgupta & Forrest 1999).

The developments within AIS are based mainly on three immunological theories, with different approaches. Clonal selection and immune networks are mainly used as learning and memory mechanisms and the negative selection principle is applied for the generation of detectors that are capable of classifying changes in self, normal behaviours. Antibody plays the role of a pattern to be found, and AIS could be compared to a robust and adaptive pattern recognition system (Timmis et al. 2008).

The antibodies (patters) are randomly generated and submitted to a training phase. The algorithms based on clonal selection reproduces those B-cell that have been successful in identifying an antigen, accelerating the response of the system and acting as system memory (learning processing) (Dasgupta & Forrest 1999) (Aickelin & Dasgupta 2005)(Dasgupta 2006).

Negative selection algorithms, on the other hand, eliminate the antibodies (patterns) that represents a "self" characteristic, or a normal behaviour, so the remained antibodies could find only patterns related to abnormal behaviour, avoiding the recognition of a "self" structure as invaders (Dasgupta & Forrest 1999) (Castro & Zuben 1999)(Aickelin & Dasgupta 2005)(Dasgupta 2006).

Use of AIS in maintenance have awaken an increasing interest by the research community (Lee et al. 2011b)(Zuccolotto et al. 2013b). Fault detection and diagnose are performed by Clonal selection algorithms (Clonalg) in electric motors (Somayaji et al. 1997) and rotational machines (Dasgupta et al. 2011) and by Negative Selection Algorithms (NSA) in analog electronic systems (Aickelin & Dasgupta 2005) and in a DC motor (Dasgupta 2006).

3. ARTIFICIAL IMMUNE INTELLIGENT MAINTENANCE SYSTEM

The aspects that appear more frequently in the literature related to industrial applications of AIS are : Focus on a single part or equipment, thus neglecting the natural distributed behaviour of the AIS; Better detection performance that other traditional methods, but larger detection rate of false positives, when applied as abnormal detectors (unknown fault-modes) (Laurentys et al. 2011); Learning occurs just in the training stage or in the early operation stages(Gong et al. 2009).

Artificial Immune Intelligent Maintenance System (AI2MS) is a distributed, multi-level IMS proposed by Zuccolotto et al in (Zuccolotto et al. 2013a) to explore the advantages of the distributed nature, pattern recognition and learning capabilities of the AIS

The AI2MS intends to provide diagnostic and prognostics of failures occurring in plant devices, applying a concept of continuous learning process and collaborative diagnostics.

A Multi Agent System (MAS) approach has been chosen to model and implement the architecture proposed, due to the autonomous, distributed and communication features, matching the needs of the AIS and distributed applications (Ramachandran et al. 2011)(Dasgupta et al. 2011).

AI2MS is composed by several different agents, each providing a specific functionality. Agents were classified in 3 layers:

- *Device Layer*: Basic layer, composed by the agents responsible for monitoring a machine or a device, described above.
- *Collaborative Layer*: Agents that promote collaboration between same device categories through information exchange regarding operation conditions and new fault modes found in the system. It is composed by the Cooperative Detection Agent (CDA), that interact with NFDA, to evaluate if the pattern detected from several machines corresponds to a new fault mode and the Evolution Agent, responsible for promoting NFDA to a FDA.
- *Plant Layer*: Plant maintenance manager layer, composed by the Plant Health Assessment Agent (PHAA), responsible to evaluate the "health" of a plant and to interface with a production supervisor system, the Failure Mode Update Agent (FMUA), to share data in case of poor data connection and Update Training Agent (UTA), to collect training data within the system.

First stage of the AI2MS development is the implementation of the Device Layer and the Evolution Agent, responsible to perform the Fault Detection Training.

3.1 Device Layer Agents

Device Layer is the primary layer, provides features of fault detection and device health assessment on a single device Figure 1 depicts the agents of this layer, relationships among them, the physical parts of a device and some communication events.

Sensors Agents (SA): A SA is linked to a physical sensor that monitors one or more parts of a device. SA provides data basically to (New)Fault Detection Agents, but also to Device Health Assessment Agent and Update Training Agent. SA is always a source of unprocessed data, but also, if necessary, it can provide data with feature extraction, like wavelet packet energy coefficients, Fourier transform coefficient, RMS value and others signals.

Sensor Diagnostic Agents (SDA) are linked to Sensor Agent, to supervise them and, in case of malfunction, inform to attached (N)FDA that data should be fixed or discarded, and to request maintenance to DHAA.

Fault Detection Agents (FDA) and *New Fault Detection Agents (NFDA)* are responsible for fault detection and diagnose of specific parts. (N)FDA links to SAs that monitor the assigned part, and have a sensor fusion capability, aggregating information from many SAs to evaluate the degradation level of a specific part. In case of failure detection (N)FDA reports to DHAA and requests a maintenance action. FDA searches known fault modes and NFDA searches unknown fault modes into a single machine while Cooperative Detection Agent (CDA) works with different machines.

If a failure is found, Collaborative Agents try to figure out whether this is a new fault mode or a normal behaviour. If a new fault mode is confirmed by several detections, an interaction with the Evolution Agent could promote this NFDA to a FDA, and the fault mode incorporated to the knowledge database.

(New)Fault Detection Agents have mobility, i.e., could migrate from one device to another. This is a fast way to share acquired knowledge, to improve the adaptability of the system and to manage the hardware resources needed to run the system.

Device Health Assessment Agent is responsible for the health evaluation of the device, forecasting the RUL and requesting maintenance services when needed. It can also request changes on device operation mode, in order to avoid a breakdown or to extend the RUL if the maintenance request cannot be accomplished in the estimated time. Each device has one DHAA, which interacts with all agents in the device and with the Plant Health Assessment Agent, responsible to manage the overall plant maintenance. DHAA also manages hardware resources (memory, processor availability) regulate the number of agents running on the device.

Evolution Agent (EA) is part of Collaborative Layer and it is the trainer agent, responsible to create and categorize the diagnose agents into the FDA and NFDA categories. It's also responsible to incorporate the knowledge acquired by the NFDA and validate by the *Cooperative Detection Agent*, as also optimize the pattern set, to increase the detection rate.

4. AI2MS IMPLEMENTATION

The implementation of AI2MS is being carried out using the JADE framework, a FIPA compliant MAS platform. JADE provides the basic services (DF) for distributed peer-to-peer applications over wired and wireless environment, and allows each agent to dynamically discover others agents (Yellow Pages services) to establish a peer-to-peer communication, among others features (Bellifemine et al. 2008).

4.1 Services and Agent Behaviours

In the Device Layer of AI2MS, the SensorAgents, its associated SDAs and the DHAA are attached to the device, the system must have at least one Evolution Agent and the FDAs and NFDAs has a dynamically "presence", in the sense that NFDAs could be created to search for new fault modes, FDAs could clone themselves and migrate to other devices, behaviours related to the "health" of the device, as antibodies in a human body. Based on this arrangement, at the first stage of design, SA, SDA, DHAA and EA could be seen more as service providers, and the (N)FDA more as an autonomous agent. Evolution Agent will be responsible only for the training of diagnostic agents, while those creation will be requested by DHAA. Those approaches are adopted to simplify the behavioural description of the agents at initial design stage.

The main services available at Device Layer are presented in Table 1 and 2. All services are triggered by a REQUEST message except for the DataProvider, a cyclic service triggered by SUBSCRIPTION and TrainingRequest, that make use of CONTRACTNET protocol.

The table 3 resume the (New)FaultDetectionAgents behaviours, that describes the diagnostic agents actions. Migrate and collaborative actions are not incorporated at this stage.

Table 1 –SA services

Agent	**SA**	**SA**	**SDA**
Service	DataProvider	SpotData Provider	SensorDiag
Inputs	---	Request Data Message	ReportDiag
Outputs	CycData Message	Response Data Message	Sensor ReliabilityMessage
Pre-condition	(N)FDA subscritpted	--	AS autodiag
Post-condition			RequestMaintenance

Table 2 – EA and DHAA services

Agent	**EA**	DHAA	DHAA
Service	DiagnosticAgentTraining	Request Maintenance	FDRegister
Inputs	TrainingRequestMessage	FailDetected Messsage	ContractDetection Messsage
Outputs	ClassificationMessage	Maintenance Request Message	--
Pre-condition	(N)FDA creation		
Post-condition			New entry on detectors

Table 3 – (N)FDA Behaviours

Behaviour	**Condition**	**Description**
GetTraining()	Agent creation	Search for EvolutionAgent and request training.
SubscribeSA()	trained	Find the DHAA and announce its presence. Search SAs, call Request Subscription protocol. Find related SDA and call RequestDiag to check the fidelity of SA data.
GetCV()	subscribed	On CycData Messages arriving, search for fault patterns. Call InformHealth protocol and, if there is a hit, call FailDetected protocol.

4.2 Protocols and message exchange

AI2MS are meant to be a heterogeneous system in the sense that various platforms based on different hardware can support agent execution. Interoperability among different agent implementations can be achieved using standard communication protocols and open data formats. These requirements lead to the adoption of FIPA Interaction Protocols and ontology to establish communication among agents. In order to implement the ontology as language codec the SL content language, was chosen because it is more compact than XML content language but still human readable, simplifying the debug process.

The message definitions are presented in the tables 4 to 7, organized by the agent interaction relations. Operational level interactions among the AI2MS agents, and auxiliary services like directory facilitator (DF) and agent management system (AMS), as registration and directory search, are not described, although used.

Table 4 - SA /(N)FDA Interactions

ACL Message	RequestSubscription	CycData
Sender	(N)FDA	SA
Receiver	SA	(N)FDA
FIPA Perform	SUBSCRIBE	INFORM
Protocol	FSsubscription	DataInform
Content	DataFormat	SignalData

Table 5 - SA /DHAA Interactions

ACL Message	RequestData	ResponseData
Sender	DHAA	SA
Receiver	SA	DHAA
FIPA Perform	REQUEST	RESPONSE
Protocol	DataRequest	DataResponse
Content	DataFormat	SpotData

Table 6 – (N)FDA/DHAA Interactions

ACL Message	InformHealt	FailDetected	InformPres ebnce
Sender	(N)FDA	(N)FDA	(N)FDA
Receiver	DHAA	DHAA	DHAA
FIPA Perform	INFORM	REQUEST	REQUEST
Protocol	HealthInfor m	Maintenance Request	Permission Request
Content	CVdata	FailData	FailSpec

Table 7 – (N)FDA/DHAA/EA Interactions

ACL Message	RequestAg ent	TrainingRe quest	TrainingRespo nse
Sender	DHAA	(N)FDA	EA
Receiver	EA	EA	(N)FDA
FIPA Perform	REQUEST	CONTRA CTNET	RESPONSE
Protocol	DiagnoseA gentReque st	TrainingRe quest	TrainingRespo nse
Content	DAcategor y		FaultMode / DAcategory

4.3 Signals, afinity function and fault modes creation

IMS needs to monitor physical variables in order to measure the degradation of a part or equipment. These signals must be transformed in other mathematical domains that enhance the characteristic related to performance of the part or device. Data processing is related to the nature of signal (vibration, electrical current) and the device measured (bearing, power source). To diagnostic proposes, this processed signal is called Performance Signature (PS), represented by a vector of real values with length N. The Fault Mode (FM), on the other hand, represents a failure signature, a vector with the same size of PS, with and extra field, r, representing the space covered by this particular FM, measured by Euclidian distance.

Generation of FaultMode are based on Variable Radius Negative Selection Algorithm (VRNSA), presented by (Laurentys et al. 2010a) and performed by the EA.

VRNSA assumes that the all “self-space” (SS), PSs related to normal behaviour, are known and each PS outside this space represent a FaultMode. New FaultModes are randomly generated and r is expanded to touch SS, creating a new detector.

AI2MS assume that there is a Self-Space known, a FaultMode Space also known, and the space between these two is the space-unknown, that could represent NewFaultModes. At the training stage, Evolution Agent builds a minimal set of FaultModes and Self-space, based on well-known signals previous acquired. When a DHAA request a defined number of diagnose agent, the Evolution Agent at first generate the FDA agents. When all FDA are generated, at each new diagnostic agent requested, a random FaultMode is generated and fitted into the space-unknown, producing a NewFaultDetectionAgent.

5. CASE STUDY

The case study for this work is an electric valve actuator model CS06, producer by Coester, a partner Brazilian company.

The Fig 1 shows the test bench used to acquire data to training and test the system. In the high left corner, highlights on the vibration sensor, positioned in the bearing of the motor shaft. This sensor provides information to the Sensor Agent.

A set of three gears were used to acquire training and test data, a normal one, a gear with high wear representing Fault1 and a heavy damaged gear, the Fault 2.

Wavelet Packet Energy (WPE) is the data processing used to generate the PerformanceSignature. WPE was pointed by (Qiu et al. 2006) as an effective method to extraction of week fault signatures from a bearing signal. Mother-wavelet Daubechies 6 achieved satisfactory results in previous works of (Gonçalves et al. 2011) and (Piccoli et al. 2012). A decomposition level of 4 was chosen, generating a PS of 16 elements. Figure 2 shows a signal and its Performing signature representing a normal behaviour while figure 3 presents a signal representing a degraded gear.

Fig. 1 - Device test bench. Detail of sensor positioning in the left upper corner.

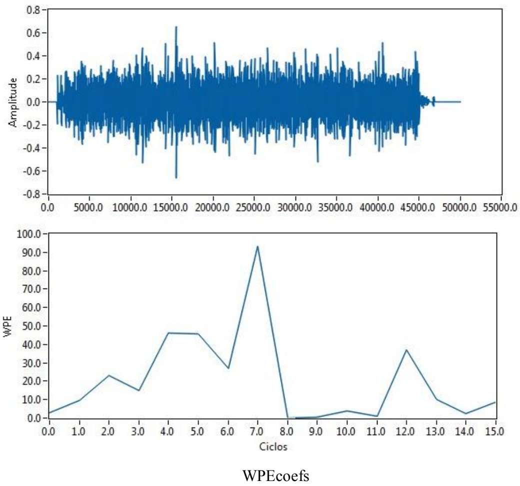

Fig. 2 – Sample of a normal behaviour signal with its PS

The data set available is composed by 150 cycles of operation, witch 50 operations representing normal behaviour, 50 representing Fault 1 and 50 Fault 2.

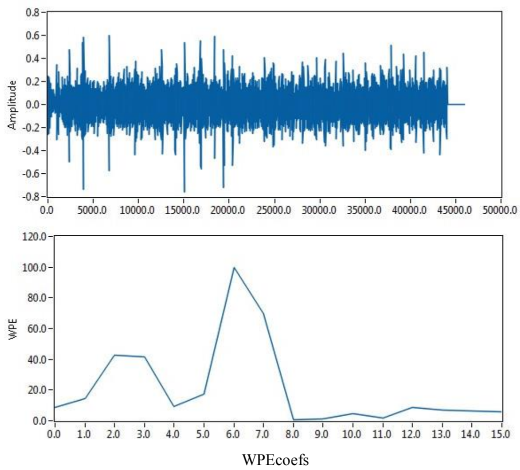

Fig. 3 – Sample of a fault mode signal with its PS

5. RESULTS

Tests were performed to verify the ability of fault identification of the Diagnostic Agents implemented.

Application based on the case study was developed to simulate the behaviour. Sensor signals are provided by data files. The system was configured to generate 50 Diagnostic Agents

A set of 20 cycles of each operational condition was randomly chosen to compose the SS and the two sets of known FM. The remaining 90 signals (30 of each type) where used to test the system. Table 1 presents the results.

Table 8. Performance of Diagnose Agents

Signal Type	Faults detected		
	Fault1	Fault2	NewFaultModes
Normal	1	0	3
Gear wear (Fault 1)	26	1	3
Gear damaged (Fault	2	24	4

6. CONCLUSIONS

This paper presents the early stages of development of new Distributed IMS using Artificial Immune Systems (AIS) concepts, with focus on the Diagnostic Agents and the methods used to recognize the fault modes.

The first test of proposed diagnose algorithm have produced 1,1% of false positives, 3,3% of false negatives(wrong diagnostic) and 11% of inconclusive results, worst outcome compared with (Laurentys et al. 2010b). The main difference is that, in the case presented, the SS is not fully defined and there is not a collaborative mechanism implemented, so is not possible at moment evaluated if the NewFalultModes identified represents an actual Fault.

Another important point is the preprocessing of known FM. Appling the VRNSA on the initial FaultMode for FDA could reduce the number of FM required for the same fault coverage and reduce the system memory requirements.

One of the needs identified during the development of multi-agent systems is the adoption of a tool that integrates modeling and code generation. Small changes in the model may require considerably time to coding and re-testing.

It is also evident that, due to the multitude of agents and the multiplicity of interaction among them, the AI2MS architecture is quite complex leading to a certain difficulty in the prediction of the behaviour of the single device and, at a higher level, of the whole maintenance system. Replicating the same harmony of its natural counterpart, where it gets its inspiration, is a great challenge for future research works along this stream.

The following activities will be carried out to further with development of the system are:

- Implementing a feedback mechanism to EA, giving learning capabilities to the system.

- Modelling and implementation of the Colaborative Diagnostic Agent, to validate the collaborative approach proposed.
- Analysis of the intensity and quality of the message exchange, to evaluate the requirements to the network support and the possibility of integration with the plant control network.
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