Distributed Fault Diagnosis using Bayesian Reasoning in MAGNETO

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***Abstract*—Many of the emerging telecom services make use of Outer Edge Networks, in particular Home Area Networks. The configuration and maintenance of such services may not be under full control of the telecom operator which still needs to guarantee the service quality experienced by the consumer. Diagnosing service faults in these scenarios becomes especially difficult since there may be not full visibility between different domains. This paper describes the fault diagnosis solution developed in the MAGNETO project, based on the application of Bayesian Inference to deal with the uncertainty. It also takes advantage of a distributed framework to deploy diagnosis components in the different domains and network elements involved, spanning both the telecom operator and the Outer Edge networks. In addition, MAGNETO features self-learning capabilities to automatically improve diagnosis knowledge over time and a partition mechanism that allows breaking down the overall diagnosis knowledge into smaller subsets. The MAGNETO solution has been prototyped and adapted to a particular outer edge scenario, and has been further validated on a real testbed. Evaluation of the results shows the potential of our approach to deal with fault management of outer edge networks.**

***Index Terms*—Bayesian inference, distributed fault diagnosis, outer edge, agents, self-learning**

I. Introduction

Telecommunication networks are growing every day in complexity and in heterogeneity. This phenomenon increases the complexity of network management. These management systems have to work with incomplete data, handle uncertain situations and deal with dynamic topologies. The number of peripheral or Outer Edge networks, like corporative and residential ones (Home Area Network, HAN), increases at a tremendous rate. Thus, an enormous variety of devices and services has to be managed. Furthermore, there is another extra problem that is the infrastructure is not completely controlled by the principal provider.

Traditionally, Operation Support Systems (OSSs) present a centralized structure. They have used quite sophisticated and expensive algorithmic techniques and have been managed by high qualified human operators. The failure root cause identification process usually is slow and complex. To reduce the requirement of human interaction during diagnosis processes and the limitations of centralised systems, there are several approaches to solve the problem of automatic Fault Diagnosis (FD) based on distributed architectures, like [1] that develops a network management system for the IPTV service to monitor and control network elements deployed in the carrier's head end, core network, access network and home network.

While [2] presents the application of a multi-agent architecture to maintenance systems that improves the consistency of policy states in decentralized autonomic network management systems; there are other approaches dealing with the multi-agent system paradigm as, for example, [3] which proposes a multi-agent system to manage networks with a distributed approach.

Furthermore, other issues must be taken into account when developing an autonomic management framework, such as the reasoning technique to process all distributed data and events from the networks. Daili Zhang [4] presents a Multiply Sectioned-Bayesian Network approach to develop a control system in large-scale complex systems. The use of this probabilistic approach allows to perform self-learning algorithms [5] to adapt the behaviour of the system to possible changes in the environment.

The previous approaches either present problems to handle uncertainty [1] or have a great complexity [4]. This paper shows an approach that tries to combine the best elements of each of previous works. The proposed approach uses a multi-agent system for FD using a probabilistic reasoning. The distributed reasoning method is simpler than [4] in order to reduce the complexity of the final system.

This paper is devoted to the description of the FD functionality developed in the MAGNETO project [6], emphasising how it has been applied to different use cases and the evaluation of the results achieved. It is organised as follows: section II gives an overview of the MAGNETO project, section III presents the approached followed in MAGNETO to solve the problem of FD, section IV describes how this approach has been used for a particular service scenario and section V explains the evaluation results. Finally, section VI highlights the main conclusions and proposes additional research activities.

II. MAGNETO overview

MAGNETO, a CELTIC Initiative project, deals with the management of Outer Edge Networks, in particular Home Area Networks (HANs). In order to set the appropriate context, the project has defined a multimedia sharing service called Omnipresent Virtual Service (OVN). This service allows free multimedia content sharing between residential users, relying on the communications infrastructure provided by a MAGNETO Service Provider (MSP), which is an ISP that provides and manages the OVN service. The focus of MAGNETO is not in actually delivering the OVN service itself, but rather on the service assurance issues derived from it. Thus, the OVN is used as an example that allows researching relevant management topics which are common to other similar services. The main topics addressed by MAGNETO cover distributed event processing, autonomic networking, FD and service assurance (Fig. 1).

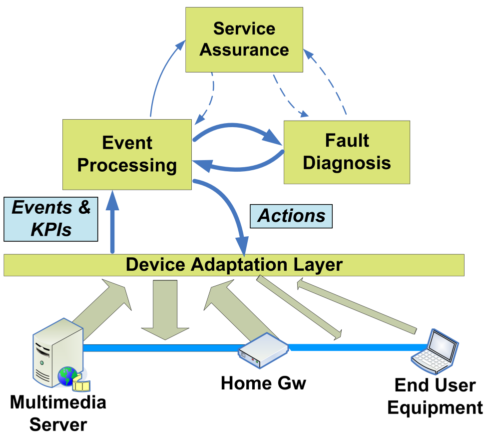

Fig. 1. MAGNETO Control Loop

As can be seen in Fig. 3, the MAGNETO scenario is composed mainly by two different HANs which are interconnected through an Internet Service Provider network. These two HANs are part of an OVN service, one acting as a provider and the other as a consumer (or user) of multimedia content. Inside each of the OVN HANs there is a Home Gateway (HG) that is in charge of both connecting the HAN to the MSP network and of management tasks. The OVN Provider HAN also hosts a dedicated multimedia server to deliver video content to consumers by means of IPTV, while the OVN Consumer HAN contains a multimedia client to consume these contents. In addition, the MSP hosts FD modules that communicate with similar modules in both HANs in order to cooperatively manage the OVN service.

MAGNETO, and in particular its FD functionality, have been already described in previous works [7], [8], [9], [10]. This paper goes one step further and provides a detailed analysis of the FD prototype together with an evaluation of the test results obtained in a real testbed.

III. MAGNETO Fault Diagnosis Framework

The goal of MAGNETO FD is to automatically find the root cause of service affecting problems. It is conceived as a distributed functionality that is accomplished by means of specialized agents distributed across different network domains that collaborate in order to come up with a common goal: the diagnosis of network and service problems. In addition, it relies on the application of Bayesian Networks (BN) technology to model the relationship between causes and symptoms of problems in a probabilistic way. The result of a diagnosis process is presented as an ordered list of the most probable causes of error together with their probabilities.

Two important challenges of FD in MAGNETO are its distributed nature, where several domains can cooperate to diagnose a single problem, and its self-learning capabilities. To address the first challenge, mechanisms to partition BNs, relying on a Multi Agent Systems approach have been investigated. Self-learning is achieved by applying appropriate algorithms to a bunch of past diagnoses in order to improve the quality of the BN.

In the next paragraphs the main capabilities of the FD framework are briefly described.

A. Diagnosis Procedure

FD is designed as a recursive algorithm in which MAGNETO performs Bayesian inference with all available evidence until either it reaches a given predefined confidence level or no more status information can be found. While the confidence in all hypotheses is below a given threshold, FD tries to gather additional information by performing tests or requesting partial inference to specific agents. From all the set of possible tests that can be performed, the one with the largest difference between value (expected increase in the confidence of the diagnosis) and cost (estimation of the cost of performing a given test in terms of resources used, time consumed, price, etc.) is chosen first.

B. Partitioning of Bayesian networks

In order to efficiently distribute inference intelligence to the different domains involved in FD, MAGNETO breaks down the overall diagnosis BN into smaller pieces (called clusters or subnetworks) so that each agent only needs to be aware of and reason on a fragment of the diagnosis knowledge (modelled as one original BN), while the complete diagnosis is done by cooperative inference involving several agents. Thus, some agents are specialized in diagnosing HAN errors while others in diagnosing ISP connectivity errors, and they further exchange their results, using the Virtual Evidence Method [11], to cooperatively reach a valid diagnosis. This method presents the advantage to be quite simple, but it has some restrictions that deal with adaptation capabilities. The use of this method establishes a static agent topology in the system. For example, agents creation and deployment in real time is an interesting task. But it is really difficult to keep coherence and consistency in the reasoning process when new agents suddenly appear or disappear in the system.

As the BN is partitioned according to the physical network topology, this method enables smoothly mapping the diagnosis process to the different network domains involved.

C. Self-learning

According to the approach followed by MAGNETO, the initial structure and Conditional Probability Tables (CPTs) of the BNs used for diagnosing service faults are modeled with the help of service operators since they usually have deep knowledge of the problem domain. In addition, self-learning capabilities have been incorporated to the FD functionality to improve its diagnostic intelligence and to adapt it to the different HAN deployments. In order to do so, diagnosis results have to be manually validated, since automatic validation is left out of the scope of the project.

Although self-learning could be conducted locally in each HAN, the selected approach is to store information about diagnosis results in a central repository located in a MSP server. This way the learning algorithm is executed on a larger diagnoses base yielding more accurate results.

Fig. 2 shows how the FD learning loop is accomplished in MAGNETO by means of the Knowledge agent. This agent performs periodically a self-learning process taking as input data the validated diagnosis results placed in the central repository and the most up to date BN knowledge. Once a new BN knowledge is obtained, new inference knowledge is properly propagated to all diagnosis agents.

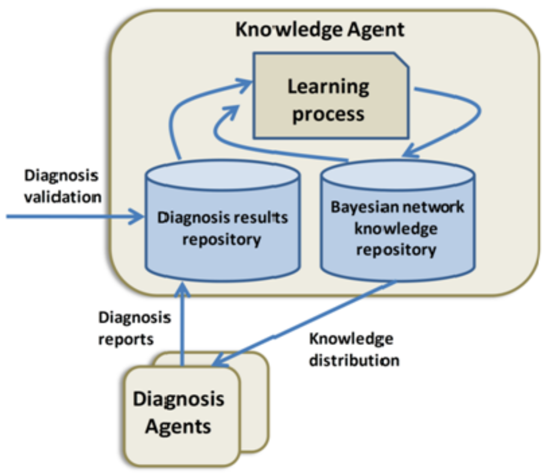

Fig. 2. Fault Diagnosis Learning Loop in MAGNETO

The self-learning process makes use of a parametric Bayesian learning algorithm, called Expectation Maximization (EM) [12] to obtain more accurate CPTs. This algorithm uses an overall confidence parameter that represents the influence of the current BN parameters in the learning process. Thus it expresses the confidence on the accuracy of the current BN as a whole over new diagnostic information and consequently the weight this new information should have in the updated BN.

It must be noted that when BN partitioning is used in MAGNETO the self-learning algorithm operates upon the overall Bayesian knowledge. Once the new CPTs are calculated, a procedure to split up the whole BN into the corresponding clusters is executed before propagating new diagnosis knowledge to the appropriate agents.

IV. Fault Diagnosis for the OVN service

Fault management modules are spread across different domains. OVN Provider and OVN User domains try to diagnose problems locally, but may need the collaboration of other FD modules in the MSP domain to complete the process successfully. Also, fault management is triggered upon detection of service errors, and the output of the FD may be collected by other modules in charge of taking actions.

A. Use cases

FD in the OVN service focuses on three main use cases: access problems, service breakdown and quality of service degradation. The main difference between the use cases is the event that triggers the automatic FD: In the service access error use case, an OVN consumer tries to establish a video streaming session with the VoD server at the OVN Provider HAN, but an error occurs at the establishment phase. In the service breakdown use case an OVN consumer watching a video from the VoD server at the OVN Provider HAN experiments a service breakdown (i.e. the video stops). Finally, the quality of service degradation use case is triggered by a quality of service degradation, resulting in a very poor quality of service delivery. In all these use cases, a FD procedure is automatically triggered when MAGNETO detects problems in the service access or in the service delivery, and once the diagnosis is finished, its result is propagated to other MAGNETO components. This way, the consumer can be notified of the problem detected, together with the recommended action. Also, the MSP operator can see all diagnosis reports stored in a common central repository, and can validate the results to enhance future diagnosis.

B. Bayesian Model

A unique BN has been modeled to diagnose the three use cases. This BN contains the relationship between the observations that can be gathered from the OVN and the different fault root causes that the diagnosis procedure can conclude. Examples of different root causes for the OVN scenario, grouped by domain, are listed below:

1) Faults at the Consumer HAN: network congestion, home gateway misconfiguration, LAN connectivity problems, etc.
2) Faults at the ISP: routing problems, congestion, etc.
3) Faults at the Provider HAN: network congestion, home gateway misconfiguration, LAN connectivity problems, OVN misconfigurations, VoD server problems, etc.

The different root causes MAGNETO is able to diagnose are modeled as hypothesis nodes. Auxiliary nodes have been used to group these hypotheses nodes depending on the domain they belong to. Thus, these auxiliary nodes represent the probability that the fault resides within a problem of the ISP or a problem in either the consumer or the provider HAN. This categorization is not completely necessary, but it is very helpful when partitioning the BN knowledge between the HAN and MSP domains.

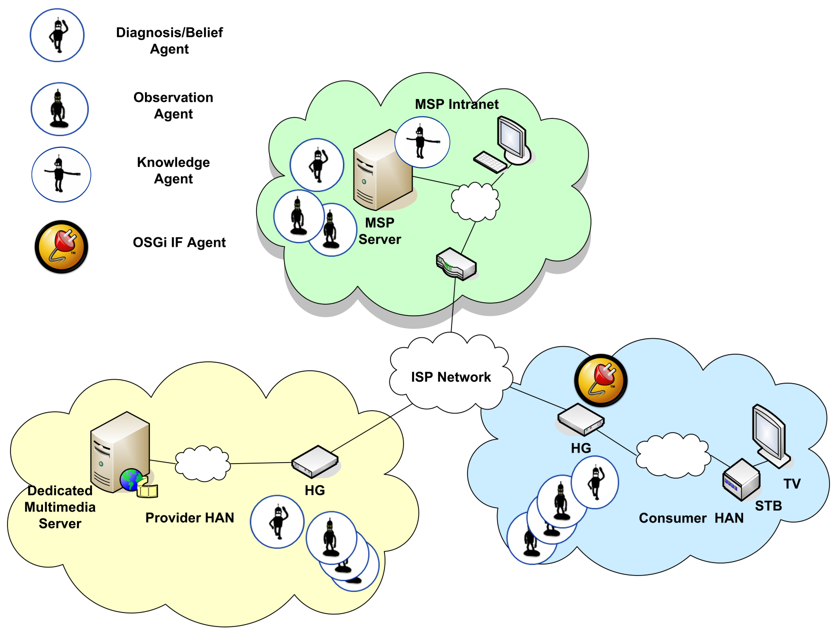

Fig. 3. Mapping of the FD functionality to the MAGNETO scenario

On the other hand, the evidence that MAGNETO uses to infer a diagnostic result are modeled in the BN as observation nodes. In particular, the observation ServiceErrorCode represents the error contained in the service error event received by the FD. The value of this node varies depending on the use case, i.e. whether the consumer is accessing or consuming the VoD service (as explained in the use description). Also, there are observation nodes to represent the result of communication tests performed at different network domains, VoD service tests, device status queries, etc.

The previously described BN knowledge used in MAGNETO is partitioned between the three network domains involved.

C. Architecture

MAGNETO FD functional block relies on a distributed multi agent architecture which allows deploying its functionality in different devices and network domains.

In order to implement this distributed FD framework, the WADE/JADE multi-agent architecture is used [13]. JADE is FIPA [14] compliant and it is completely implemented in Java. WADE runs on top of JADE and provides important mechanisms to facilitate the management of the agent platform.

Deployment of MAGNETO components in the HGs is based on the OSGI architecture [15]. To allow this, FD agents located in each HG rely on the JADE-OSGi framework. On the contrary, FD agents deployed in the MSP can be deployed as a WADE application. This allows taking advantage of the enhancements provided by WADE while being able to communicate with FD agents in the HANs.

Fig. 3 depicts the distribution of FD agents in the different network domains. There are different types of diagnosis agents which are briefly described below:

- OSGI interface agents: They communicate FD with other MAGNETO components. Upon reception of Service Error events, they start a diagnosis procedure and, once a diagnosis report is obtained, they propagate it back to other MAGNETO components as a DiagnosisReportEvent, and to a Storage agent, located within the MSP.
- Diagnosis agents: A diagnosis agent receives diagnosis requests, together with observations available for the diagnosis. Then it creates its own BN and fills it with the evidence it has for the given request and the related evidence it may have in its cache. It then infers the new probabilities and tries to come up with the cause of the problem. If it needs further evidence to reach a conclusion, it may request additional observations/evidences to Observation Agents. In addition to observations, they may also request beliefs on a particular Bayesian node state to Belief Agents. In MAGNETO there is a single diagnosis agent which is located in the Consumer HAN. It makes use of the local observation agents to gather all possible local observations, and further requests beliefs to the belief agents located in the MSP and the remote HAN to diagnose VoD errors.
- Observation agents: They provide observations by performing specific tests upon request. In the OVN scenario, there are observation agents, such as connectivity agents, deployed in all three domains. Depending on the domain, they can provide a specific BN observation. Other example of observation agents, located within the OVN HAN provider, make specific VoD server tests, check the OVN configuration, etc.
- Belief agents: They provide a belief on a certain node state. Like the diagnosis agents, they also have their own BN and make Bayesian inference to obtain the requested

belief. The main difference with diagnosis agents is that they just provide the belief (or probability) on the status of a particular node, rather than providing a whole diagnosis report. In the OVN scenario there are two belief agents: the ISP and the Provider Belief Agents. Each of them provides the belief that the cause of the problem resides in an ISP or in a Provider HAN problem respectively.

- Knowledge agent: The knowledge agent is in charge of distributing diagnosis knowledge to all interested agents and performing Self Learning by processing the results of past diagnoses.
- Storage agent: This agent is in charge of storing diagnosis reports in a central repository.

Besides the agents previously mentioned, the MAGNETO FD functionality provides:

- A common repository database where all diagnosis reports are stored, as well as relevant information about their validation.
- A web interface to browse all diagnosis stored in the repository, as well as to manually validate them.

D. Interfaces

1) OSGi interface: FD communicates with other MAGNETO modules located in the HG by means of notifications, using the subscribe/publish services provided by the EventAdmin OSGI bundle. Thus it subscribes to VoD Service Error Events such as service access timeouts, service breakdowns (for instance, the video client stops receiving any packets from the multimedia server), service bad quality events (packet loss or jitter in the video stream), etc.

These events are used to set the value of the ServiceErrorCode node of the BN during the diagnosis procedure. Once this procedure ends, the FD publishes a DiagnosisReportEvent. This event contains all information included in the ServiceErrorEvent, all observations gathered and used for the actual diagnosis, and the result of the diagnosis given as a list of beliefs showing the root causes that exceed a configured percentage value (for instance above 60%) together with their probability.

2) GUI interface: The results of the diagnosis process are stored in a Data Base installed in the MSP server. To allow MSP operators accessing information about past diagnoses, a graphical user interface has been implemented by means of a web application that runs on the MSP server. This GUI interface allows the operators to query diagnosis results, view diagnosis details and validate diagnosis reports. Note this functionality is needed to enable self-learning in the FD application.

V. Evaluation

In order to validate MAGNETO results, a real testbed has been deployed, consisting of the following main parts:

- OVN Provider HAN: it is the HAN providing the multimedia content and must thus host a multimedia server.
- OVN Consumer HAN: it is the HAN consuming the service and must thus host a multimedia client.
- MSP Intranet. It simulates a LAN belonging to the MAGNETO service provider that includes both MSP's servers hosting the MAGNETO components.
- ISP Network. One or several real ISPs providing Internet access to home users. In our testbed, it is just a switch and 100 MB links connecting the other elements.

Note each HAN has a HG, which is a MAGNETO Enabled Device (i.e. a device with the capability to run MAGNETO software). In MAGNETO, HGs are simulated using a switch and a regular Linux PC, with two Ethernet adapters. The MAGNETO server inside the MSP Intranet is also a MAGNETO Enabled Device. In addition, the iptables tool is used to simulate traffic congestion in different points of the network by intentionally dropping IP packets.

After deploying MAGNETO on this testbed, a comprehensive test plan has been passed to validate the FD functionality. Tests related to FD have been grouped in three main categories: validation of the diagnosis results for the use cases prototyped, partitioning of the BN and analysis of the self-learning algorithm behaviour for different combinations of parameters.

Based on a detailed analysis of the test results, a complete evaluation has been conducted whose main conclusions are described in the following paragraphs:

A. Achievements

The fact that FD in MAGNETO relies on a Multi-Agent System facilitates easy deployment of agents in the different domains involved. Thus access to detailed and local information that would otherwise be difficult to obtain is much easier (for instance, access to detailed status information local to a HAN). Besides, this multi agent framework scales much better than traditional centralized architectures and also enables distributed reasoning.

In addition, the FD process has been successfully validated with three different error groups: access, service breakdown and quality degradation errors. After analysing a large set of diagnosis results obtained during the MAGNETO system tests, it can be concluded that around 85% of them are correct (see section V-B for further explanation) and that the average time to finalise a diagnosis process is below one minute in 90% of the cases.

As for the self-learning algorithm, it has been successfully validated by testing different combinations of input data and configuration parameters. Main conclusions reached are as follows:

- Diagnosis validation improves the learning process. Results improve as the percentage of validated diagnoses increases. Assigning a higher weight to validated diagnoses over non validated ones also improves the learning process.It was concluded that the best results are obtained when this weight is equal 5.
- The threshold parameter used to convert probability values to Boolean ones (either a hypothesis is true or not)

during the learning process has a limited impact on its results. Best results were obtained when this threshold is around 60%.
- A high confidence parameter gives more weight to the initial BN over new diagnostic data. Depending on the level of trust the administrator has on available data and diagnostic information this parameter can be fine tuned appropriately. The value of this parameter is directly related to the advanced knowledge/experience of the human operator that designed the BN, so it is not possible to establish a global value.

B. Issues

The way partitioning of BNs works in MAGNETO implies topology restrictions. This could be improved by using more elaborate mechanisms (collaborative algorithms) as those proposed by the Multiply Sectioned Bayesian Networks [16] approach that ensure consistency through heavy messaging at the cost of decreasing the overall system performance.

Since in MAGNETO the BN is manually created from scratch, based on experts' feedback, the resulting model is highly error prone. This is the reason why some of the diagnostic results obtained during the evaluation slightly differ from the ideal value that would be expected in a real production system. A solution to this problem would be to rely on a powerful self-learning process to fine tune and improve the initial manually created BN. This solution would increase the percentage of correct diagnosis (now this rate is 85%).

Self-learning relies on manual validation of diagnosis results which is an extremely cumbersome and costly process requiring active involvement of network operators. In addition, the self learning process is rather complex and depends on many different parameters. Therefore, further tests with larger data sets may be needed to better tune this process. Besides, the amount of diagnosis information available in the MAGNETO testbed is very limited. Consequently, self learning would be highly improved by using as input a large amount of reliable diagnosis information from real production environments.

VI. Conclusions and Future Work

The MAGNETO FD framework has been successfully prototyped and validated in a real testbed that emulates two interconnected HANs and a MSP. This prototype includes functionality to diagnose the most probable cause of service errors by conducting distributed inference across several domains. In addition, it has the capability to automatically improve its diagnosis knowledge base by means of self-learning algorithms.

However, a number of drawbacks and limitations have been identified that require additional research. Thus, future activities related to FD should mainly focus on the following areas:

- Automatic validation of diagnosis results to make the learning loop more efficient. This way, human intervention and related costs could be reduced to a minimum.
- Improvements to the learning algorithm. For example, by assigning an independent confidence value per parameter in a BN so only relevant data would be used to update each parameter. However, this may result in a very time consuming algorithm.
- To achieve a self-reconfigurable and more scalable management framework, more complex algorithms have to be explored, like the ones used in Multiply Sectioned Bayesian Networks.

Acknowledgements

This paper describes work undertaken in the context of the CELTIC MAGNETO project, which is partially funded by the Spanish "Ministerio de Industria, Turismo y Comercio" under the Avanza program.

References

[1] C.-H. Hu, Y.-Y. Hsu, C.-J. Hong, S.-H. Hsu, Y.-C. Lin, C.-M. Hsu, and T.-H. Fang, "Home network management for IPTV service operations - A service provider perspective," in *2010 IEEE/IFIP Network Operations and Management Symposium Workshops*. IEEE, 2010, pp. 1–7.

[2] J. C. Nobre and L. Z. Granville, "Consistency maintenance of policy states in decentralized autonomic network management," in *2010 IEEE Network Operations and Management Symposium - NOMS 2010*. IEEE, 2010, pp. 519–526.

[3] G.-z. Liu and D. Juan, "Design of Distributed Network Management System Based on Multi-agent," in *2010 Third International Symposium on Information Processing*. IEEE, Oct. 2010, pp. 433–436.

[4] D. Zhang, "Multi-agent based control of large-scale complex systems employing distributed dynamic inference engine," 2010.

[5] G. Peng and L. Naixiang, "An EM-MCMC algorithm for Bayesian structure learning," in *2009 2nd IEEE International Conference on Computer Science and Information Technology*. IEEE, 2009, pp. 158–162.

[6] "Magneto: Management of the outer edge." [Online]. Available: http://projects.celtic-initiative.org/MAGNETO

[7] A. Carrera, J. Gonzalez-Ordás, J. García-Algarra, P. Arozarena, and M. Garijo, *A Multi-agent system with Distributed Bayesian Reasoning for Network Fault Diagnosis*, ser. Advances in Intelligent and Soft Computing. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, vol. 88, pp. 113–118.

[8] P. Arozarena, R. Toribio, J. Kielthy, K. Quinn, and M. Zach, "Probabilistic Fault Diagnosis in the MAGNETO Autonomic Control Loop," in *4th International Conference on Autonomous Infrastructure, Management and Security*. Springer, Jun. 2010, pp. 102–105.

[9] J. García-Algarra, P. Arozarena, S. García-Gómez, A. Carrera-Barroso, and R. Toribio-Sardón, *A Lightweight Approach to Distributed Network Diagnosis under Uncertainty*, ser. Studies in Computational Intelligence. Springer Berlin / Heidelberg, 2011, vol. 329, pp. 95–116.

[10] J. Kielthy, K. Quinn, R. Toribio, P. Arozarena, S. Handurukande, M. Mateos, and M. Zach, *Design of a HAN Autonomic Control Loop*, ser. Lecture Notes in Computer Science. Springer Berlin / Heidelberg, 2010, vol. 6473, pp. 1–11.

[11] R. Pan, Y. Peng, and Z. Ding, "Belief update in bayesian networks using uncertain evidence," *2006 18th IEEE International Conference on Tools with Artificial Intelligence ICTAI06*, no. 3, pp. 441–444, 2006.

[12] T. Hastie, R. Tibshirani, and J. Friedman, *The elements of statistical learning: data mining, inference, and prediction*. Springer Verlag, 2009.

[13] F. Bellifemine, G. Caire, and D. Greenwood, *Developing multi-agent systems with JADE*. Wiley, 2007.

[14] IEEE Foundation for Intelligent Physical Agents, "FIPA Agent Management Specification," 2000.

[15] N. Bartlett, "OSGi in practice," *ICAME Newsletter*, vol. 11, p. 229, 2009.

[16] Y. Xiang, D. Poole, and M. P. Beddoes, "Multiply sectioned bayesian networks and junction forests for large knowledge-based systems," *Computational Intelligence*, vol. 9, no. 2, pp. 171–220, May 1993.