Semantic Correlation for Alarms Classification in Maintenance Process

(Full text in English)

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Abstract

In the scope of maintenance process, alarms triggering and management is an important issue that diagnosis assistance system must take into account. Alarms floods have always been serious risks in monitoring problem, where is overwhelm operators with large amount of alarm messages and different parameters in a short period of time. Consequently, without a useful alarm's management, diagnosticate the alarm on fly become a very hard task formaintenance operators. In order to improve alarms' management, we elaborate in this work an approach allowing the classification of alarms according to the failed equipment and using past event traces. In this context, we studied various methodologies of problem discovering and classification. Hence, we provide in this work a comparative analysis of Meta-heuristic optimization techniques using knowledge capitalization extracted thanks to an ontology. The proposed approach has been tested on a real industrial data. The obtained results are encouraging.

Keywords: metaheuristics, data classification, ontology, maintenance process, alarm management

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1. Introduction

Diagnosis process is a main activity in industrial maintenance. It is the process involving at the same time the observation of a situation (monitoring of an industrial system) and the relevant decisions to be taken following this observation. It is a vast research field interesting researchers of multiple scientific communities such as control, signal processing, statistics, artificial intelligence, machine learning, etc. A reliable and quick diagnostic with sufficient resolution is a topical challenge for industrials due to the financial impact.

Diagnosis is the process allowing the interpretation of alarms generated by controlsystems.It involves few tasks such as filtring all the effect alarms, locating the root alarms and thus identifying the root cause of the abnormality. Alarms are triggred in order to inform operator about abnormality when the behavior of an equipment doesn't much to the designed one according to some defined parameters.

In big industrial sites, alarm tregering ferequency is too large. The handling of these alarms is called alarm management. This later try to clusterize alarms by taking into account of possible correlation and to analyze the most frequent ones. JSA-18.2 standard [1] draws a lifecycle covering many stages of alarm management. Form the earlier stages, rationalization, justification and prioritization, the alarm manager should ensure that one alarm does not duplicate another alarm that is designed for the same abnormality. Most of Distributed Control Systems (DCSs) are by default ivnvolve an alarm management system that dynamically filters alarms based on an operation plan and conditions so that only the currently significant alarms are annunciated [2]. Despite that, alarm floods are always considred as serious risks in industrial process monitoring where it overwhelm operators with large amount of alarm messages raised within a short period of time as shown in (Figure 1).

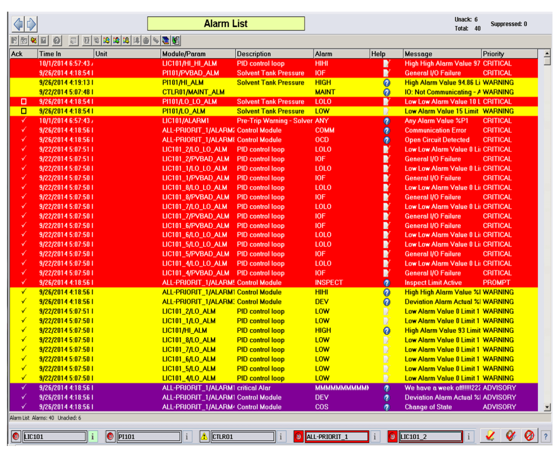


Figure 1. The flood alarm display screen

Operators (i.e. alarm managers) have to pay close attention to the boom of alarms, by identifing quickly and accurately the root cause of the abnormal situation, and then take corrective actions in order to bring the process back under control [3].

In this context, process modeling and fault detection are important for solving the pressing problem of alarm flooding [4].

On the other hand, if alarms are related each another (correlation concept) on fly, those alarms could be managed before to be sent to operators and then we can get a significant rundown of alarms number [5,6].

The aim of this research is the elaborate an approach allowing alarm correlation in pre-diagnosis phase to significantly to reduce redundant alarms and consequential avoide alarms floods. In this context, we propose a dynamic alarm classification approach based on the semantic correlation.

The rest of this paper is organized as follows: in section 2, we present a review on alarm management and filtering as well as semantic correlation. In section3, we describe the proposed methodology where we introduces some fundamental concepts regarding metaheuristics optimization approaches. The effectiveness of the contribution is explicitly presented in Section 4 which is followed by a numerical example and a real industrial case study. Conclusion will be presented in Section 5.

2. Literature review

Existing studies focuse on two main problems in alarm management:

1- False alarms; and

2- Redundant alarms or called alarm flood.

These two problems make hard of operators to dect the main causes of the abnormal events and fail to handle the root cause in time.

To address false alarm issues posed by traditional monitoring methods, Brooks [7] proposed a mathematical treatment of alarms that considers them as multi-variable interactions between process variables to calculate values for alarm thresholds. This method helps to reduce substantial false alarms. Chen [8] introduced a statistical approach constructing a second-level control limit based on known properties of statistical distributions of in and out-of-control observations. In theire survey [9], authors studied the false alarm minimization techniques in the scope of signature-based Network Intrusion Detection System 'NIDS'.

As we noted, the second main challenge in alarm management is to deal with alarm floods. It is becoming a major concerned safety issue. An alarm flood has been defined by ISA [10] 18.2 as being 10 or more alarms raised in any 10 min period per operator. In this scope few works were used event correlation analysis as wellas two-layer cause-effect model in order to reduce the number of alarms [5,11–17]. As a strategy to control alarm floods for chemical process transitions, Zhu [18] proposes an artificial immune system-based fault diagnosis 'AISFD' method and Bayesian-estimation-based dynamic alarm management 'BEDAM' method to generate useful alarms in fault situations. Takeda et al. [12] investigates a logical and systematic alarm system design method that explicitly explains the design rationales from know-why information for proper management of changes through the plant lifecycle. Hu et al.[6] proposes a method to detect correlated alarms and quantify the correlation level.

Moreover, taking into account alarms history for alarm analysis is a useful method to improve alarm management strategy especially in the case large-scale application and massive dataset [19]. In this scope, Fanti et al. [20] provide an approach by using the Unified Modelling Language and Coloured Timed Petri nets in order to modeland analyze alarms in the Integrating the Healthcare Enterprise 'IHE' Alarm Communication Management 'ACM'. Li et al. [19] proposed a distributed parallel alarm management strategy to solve the problem caused by lack of scalability and efficiency of traditional alarm management strategy in the scenario of massive and rapid growing alarm data. The proposed strategy aim to reduce alarms on the dashboards of operator station in both normal situation and alarm flooding situation.

Existing works, in particular ones described above, had successfully developed alarm management approaches thanks to the alarm filtering based on correlation and then display more accurate alarms on operator dashboards. Among that, some questions should be asked such us: are really these solutions help operators in the diagnostic process? Assuming, we get to reduce the number of alarm, what is the percentage of reduction? Is reduction does not pose a problem on the reliability of the system?

Event correlation in eisting works has been limited to syntactically identical attribute values instead of addressing semantically equivalent attribute meanings. The application of semantic alarm correlation was used with a diethanolamine (DEA) treatment unity plant, which is a very important process in the petrochemical processes industry. [21] introduces an approach that uses semantic technologies, ontologies, for the definition of event correlations to facilitate semantic event correlation derived from semantic equivalence, inherited meaning, and relationships between different terms or entities. In [22] a case study, it is presented on the advanced treatment of alarms with the objective of finding alarms correlated by time with the help of the knowledge flow of the process modeled via DEA ontology instance, which helps the search for unnecessary alarms. This study is based on learning system. Their correlation technique is based on joins and requires complex concatenations to express rich correlations between alarms. According to our research, the concept of correlation is used in different granularity, it may be according to time of appearance[22] or to root cause [23].

Thus, in most works, the correlation is based on the time of occurrence of alarms, it can happen that one equipment generates a large number of alarms, so there is no correlation that take into consideration aspects such as the concerned equipment or the prvious diagnosis' results, etc.

To recover these lacks, we think that exploring rather a semantic correlation can provide an added value. Semantic correlation according to equipment and previous experiences has not been addressed yet.

As well, we think that it is interesting to classify alarms over failed equipment before processing the correlation. Hence, the proposed work will deal with the enriched semantic correlation to launch a rapid preliminary diagnosis and also to capitalize the knowledge of monitoring stakeholders.

3. Proposed Approach

As noted above, our challenge is to develop a system that can dynamically grouping related alarms according of semantic correlation of the alarm context (equipment, history, feedback, etc.) in order to facilitate the launching of diagnosis process. In this work, we use different metaheuristics optimization methods that we adopt and adapt for the knowledge discovery process inspired from PETRA process [24] (Figure 2).

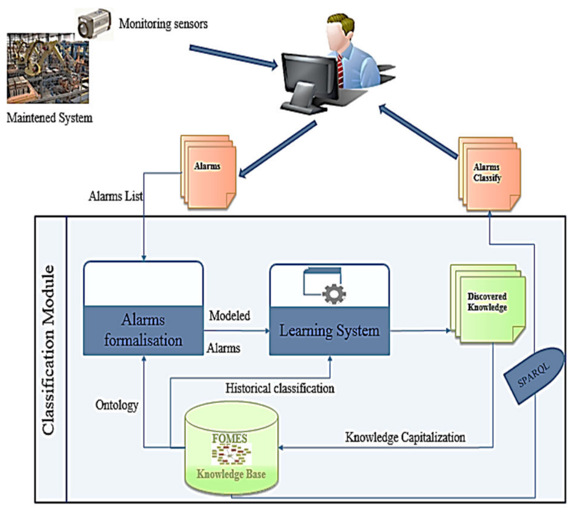


Figure 2. General scheme of the suggested alarm classification approach

Shows different steps involved in our process. The purpose is to learn more about the apparition of alarms corresponding to abnormal situation based on historical alarm data, to analyze their executions and then to extract knowledge concerning failed equipment. More details about these steps are provided in the following sections.

The knowledge base in this process is built according the maintenance domain ontology FOMES [25], which is extension of IMAMO ontology (Industrial Maintenance Management Ontology) [26] so as to model alarms as well as to interpret and extract knowledge.

The role of the alarm formalization step is to prepare the data in an adequate format for the mining operation. We build in this step an appropriate “formal context”, based on the ontological knowledge. The classification module receives new list of alarm that it parses them to present the knowledge in a structured form. After that, this list is stored in the knowledge base.

Once the alarms are structured and stored as new instances in the knowledge base, the learning phase is initiated to interpret them and extract new knowledge. So classification algorithm is trained, it can be used to classify future alarms.

3.1 Knowledge base & ontology

Alarms file includes information such as description, zone (sourced of alarm), sub-zone, level of emergency, date and time which are recorded in text or Excel files. All elements about one alarm are stored in one row record. To take advantage of the semantic aspect, a specific attention has been drawn on ontologies, ensuring that information/knowledge exchanged in the industrial system is meaningful, and that all the stakeholders interpret it in the same way [27]. It is possible to find in the literature several definitions of ontology. The most common and known is proposed by Gruber, “a formal explicit specification of a shared conceptualization. Ontology is a rigorous representation of concepts and their allowed interactions”[28]. In the simplest case, an ontology describes a hierarchy of concepts (i.e.classes) related by taxonomic relationships (is-a, part-of). In more sophisticated cases, an ontology describes domain classes, properties (or attributes) for each class, class instances (or individuals) and also the relationships that hold between class instances. It is also possible to add some logical axioms to constrain concept interpretation and express complex relationships between concepts. This basic ontological knowledge will be encoded in a simplified general model.

Figure 3 presents a part of the classes of FOMES (Feedback-CBR Ontology for Maintenance Expert Selection) which is extension of IMAMO Ontology (Industrial Maintenance Management Ontology).

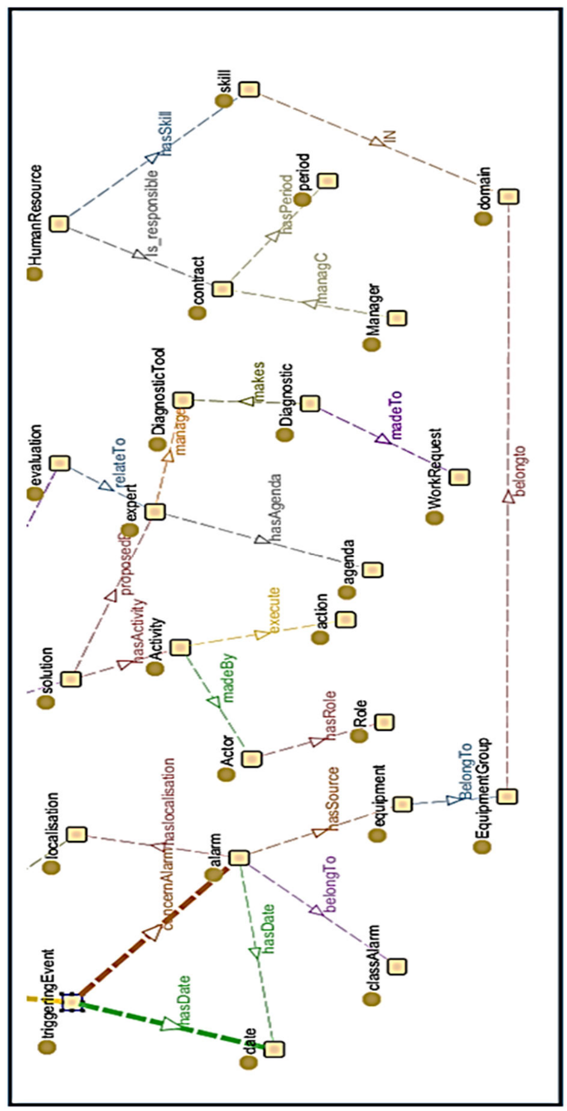


Figure 3. Part of FOMES concept under protégé (plugin Jambalaya)

A focus is made on some packages of FOMES[5] in order to adapt the ontology to our need.

The class **Alarm** is characterized by different data types such as *alarm_type*, *emergency_level*, etc. According to the requirements of the conception facility, we associated each alarm to an **Alarm_category** with the object property ***belongsTo***. The available equipments are instanciated in the class **Equipment.** Each one of these equipment is part of an **EquipmentGroup** with the object property ***belongsTo***. An object property ***belongsTo*** is associated to each **EquipmentGroup** and **Area** to make an implicit relationship between the alarm and equipment. We distinguished two type of equipment in our modeling, failed_equipment and alarm_source_equipment. In fact, we create two Object property the first ***has_source*** associates **Alarm** to **Equipment** and the second one is ***belongsTo*** which associate each **Alarm** to an **EquipmentGroup. Localization** class registers the different zones and sub-zones of an alarm with the two data types' *zone* and *sub-zone*. Object property ***has_localization*** associates each alarm to zone and sub-zone**.**

Table 1. Alarm dataset parameters

Information / Description	description of alarm: type of triggering event launched from a data acquisition system indicating that there is a measure from a sensor violating some conditions concerning a specific equipment or environment
Alarm Source	zone of alarm: position of source alarm in a production area
Alarm Source equipment	monitoring equipment:
Level of Emergency	urgent /no urgent: level of emergency alarm
Date /Time Alarm	date and time of occurrence alarm
Failed Equipment	physical equipment characterized by inability to perform a required function

3.2 Alarm transformation & formalization

This step consists of collecting all the alarms of a given recordable environment while safeguarding the diagnosis operators. An excel file saving historical alarm, but they are under the constraint of the complexity of their structure and analysis. Therefore, the transformation is made via a sequential parsing of the excel file and extraction of knowledge via a mapping with the alarm model of the ontology. Finally, the modeled alarms are stored in the knowledge base. We describe the concepts of FOMES that are exploited in our system.

3.3 Learning system (Alarm classification)

Nilson relates the definition of learning to "knowledge acquisition", "skills under-standing", "experience by reuse" and "modification of a behavior al tendency by experience" [29]. Machine learning refers to a system that can automatically acquire and integrate knowledge, a system that is able to learn from experience, training, analytical observation and other means. Thus, machine learning techniques are considered to be the heart of any learning process, to produce learned (acquired, discovered) knowledge [30][24].

Classifiers in learning process may be based on different frameworks: Bayesian networks [31–33], neural networks [34,35], decision trees [24,36], Artificial immune algorithms [37], etc. Most works haven't taken into account the gain that can be expected when integrating additional knowledge during the learning process. In this work, we focuse on a comparative of the three metaheuristics algorithm Simulated Annealing (SA), Genetic Algorithm (GA) and Particle swarm optimization (PSO) based on Alarm ontology.

We propose a comparative analysis of the three approaches, adopted to deal with the problem of alarm classification: SA, GA and PSO. Comparison of the methods was made considering the factor fitness function value. Such method highly depends on operating experience and knowledge base, because it analysis process starts with the alarm history which is a file containing all past alarm messages.

3.3.1 Simulated Annealing (SA)

SA is a well-known single-based solution metaheuristic, developed by Kirkpatrick in 1980 [38]. The main idea of SA is to imitate the annealing process's cooling schedule. SA decrease gradually the cooling process starting from a high initial temperature value, and then the cooling process is done slowly to avoid metastable states that can be accrued (local minimum). SA starts from an initial solution, and then at each cycle, a new neighbor solution is generated randomly. Neighbour that enhances the current solution is accepted with a probability that depends mainly on the change of ΔE in the fitness function and the current value of temperature.

3.3.2 Genetic Algorithm (GA)

Genetic Algorithm [39] is one of the most popular population-based search metaheuristic. GA mimics the Darwinian evolution theory and the natural selection concepts. The GA starts from a population of chromosomes (Solution) randomly initialized, then at each generation, every chromosome is underwent to selection that constitutes in choosing pairs of solution from the current population and makes them arising by means of gene crossover and mutation. The last step of the GA process is the replacement phase that determines which solutions (chromosomes) of the current population will survive to create the next generation. The GA is repeated until a stopping criterion is met (Number of generation, maximum number of the fitness the function evaluation...).

3.3.3 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is another well know population based search metaheuristic, created by kennedy in 1995 [40]. PSO belongs to the swarm intelligence optimization algorithms. It simulates the collective behavior concept of natural organisms (fish, birds…). The PSO metaheuristic begins with a population (swarm) composed of a set of particles. Each particle contains a position Xi and velocity Vi. At each iteration, particles modify their position and their velocity using the following formulation:

[5] A particular consideration was given to the IMAMO package [26] in order to adapt it to our needs.

$$X_i(t) = X_i(t-1) + V_i(t) \qquad (1)$$

$$V_i(t) = V_i(t\text{-}1) + c_1 r_1 (P_{best\,i}(t\text{-}1) + X_i(t\text{-}1)) + \\ + c_2 r_2 (G_{best\,i}(t\text{-}1) + X_i(t\text{-}1)) \qquad (2)$$

where: c1, c2 are two constants describing the cognitive attraction and the social attraction; r1, r2 are two random numbers generated between [0,1]. P_{besti}, G_{besti} are the best position obtained by the particle i and the best position ever found by the swarm respectively.

3.4 Knowledge capitalization

Capitalizing knowledge constitutes the last step in our Knowledge discovery process. The objective of this activity is to link the failed equipment generated during the learning step with the existing alarms and store them in the knowledge base. The operation of this step can be divided into two activities:

The first activity is to create an interpretation column that includes both validated alarm-category and alarms already existing in the knowledge base, generated from the learning step.

The second activity is to record the link that will be taken in relation to each generated alarm-category with instance alarm saved in KB.

4. Selection of learning algorithm

4.1 Data set description

The database used in this stady has been collected from a real Eectricity Transmission System. We note that the lack of a standardized format for historical flood alarms in this field let us to create new knowledge base based on our ontology. For training the learning system, at first step, we assumes a set of modeled alarms for preparing the classification phase. Then, we use data extracted from the knowledge base. When datasets include attributes that contain redundant data, this causes delay in building the classification model. Hence, we proposed to consider the six input variables are considered which are presented in Table 1 (*supra*).

The outputs are presented in Table 2, in which each class is related to an equipment.

Table 2. Alarm Classes

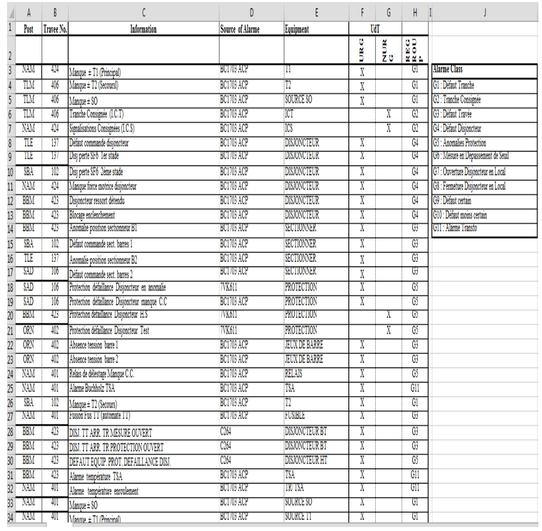
G1	T1 Source
G2	ICS
G3	BT Disjoncteur
G4	Disjoncteur
G5	Protection
G6	ICT
G7	CC Source
G8	Fuse
G9	Line
G10	TSA
G11	TR

Our dataset is composed of 700 rows of modeled alarms. Moreover, 350 of the actual data is used for training and the remaining rows are to be used for testing and comparing the three algorithms.

The output (classes) for alarm data set can takes the values '1', to '11', where:

- '1' means that the alarm belong to Group1.
- '2' means that the alarm belong to Group2.
- '3' means that the alarm belong to Group3.
- '4' means that the alarm belong to Group4, etc.

Figure 4 shows a part of the log file of Electricity Transmission System used for the application example.



	A	B	C	D	E	F	G	H	I	J
1	Post	Travee No.	Information	Source of Alarme	Equipment	UdT				
2						URG	NURG	REGROUP		
3	NAM	424	Manque ± T1 (Principal)	BC1703 ACP	T1	X		G1		Alarme Class
4	TLM	406	Manque ± T2 (Secoursl)	BC1703 ACP	T2	X		G1		G1 : Défaut Tranche
5	TLM	406	Manque ± SO	BC1703 ACP	SOURCE SO	X		G1		G2 : Tranche Consignée
6	TLM	406	Tranche Consignée (I.C.T)	BC1703 ACP	ICT		X	G2		G3 : Défaut Travée
7	NAM	424	Signalisations Consignées (I.C.S)	BC1703 ACP	ICS		X	G2		G4 : Défaut Disjoncteur
8	TLE	137	Défaut commande disjoncteur	BC1703 ACP	DISJONCTEUR	X		G4		G5 : Anomalies Protection
9	TLE	137	Disj perte SF6 1er stade	BC1703 ACP	DISJONCTEUR	X		G4		G6 : Mesure en Dépassement de Seuil
10	SBA	102	Disj perte SF6 2ème stade	BC1703 ACP	DISJONCTEUR	X		G4		G7 : Ouverture Disjoncteur en Local
11	NAM	424	Manque force motrice disjoncteur	BC1703 ACP	DISJONCTEUR	X		G4		G8 : Fermeture Disjoncteur en Local
12	BBM	423	Disjoncteur ressort détendu	BC1703 ACP	DISJONCTEUR	X		G4		G9 : Défaut certain
13	BBM	423	Blocage enclenchement	BC1703 ACP	DISJONCTEUR	X		G4		G10 : Défaut moins certain
14	BBM	423	Anomalie position sectionneur B1	BC1703 ACP	SECTIONNER	X		G3		G11 : Alarme Transfo
15	SBA	102	Défaut commande sect. barres 1	BC1703 ACP	SECTIONNER	X		G3		
16	TLE	137	Anomalie position sectionneur B2	BC1703 ACP	SECTIONNER	X		G3		
17	SAD	106	Défaut commande sect. barres 2	BC1703 ACP	SECTIONNER	X		G3		
18	SAD	106	Protection défaillance Disjoncteur en anomalie	7VK611	PROTECTION	X		G5		
19	SAD	106	Protection défaillance Disjoncteur manque C.C	BC1703 ACP	PROTECTION	X		G5		
20	BBM	423	Protection défaillance Disjoncteur H.S	7VK611	PROTECTION		X	G5		
21	ORN	402	Protection défaillance Disjoncteur Test	7VK611	PROTECTION		X	G5		
22	ORN	402	Absence tension barre 1	BC1703 ACP	JEUX DE BARRE	X		G3		
23	ORN	402	Absence tension barre 2	BC1703 ACP	JEUX DE BARRE	X		G3		
24	NAM	401	Relais de délestage Manque C.C.	BC1703 ACP	RELAIS	X		G5		
25	NAM	401	Alarme Buchholz TSA	BC1703 ACP	TSA	X		G11		
26	SBA	102	Manque ± T2 (Secours)	BC1703 ACP	T2	X		G1		
27	NAM	401	Fusion Fus TT (automate TT)	BC1703 ACP	FUSIBLE	X		G3		
28	BBM	423	DISJ. TT ARR. TR MESURE OUVERT	C264	DISJONCTEUR BT	X		G3		
29	BBM	423	DISJ. TT ARR. TR PROTECTION OUVERT	C264	DISJONCTEUR BT	X		G3		
30	BBM	423	DEFAUT EQUIP. PROT. DEFAILLANCE DISJ.	C264	DISJONCTEUR HT	X		G5		
31	BBM	423	Alarme température TSA	BC1703 ACP	TSA	X		G11		
32	NAM	401	Alarme température enroulement	BC1703 ACP	TR/ TSA	X		G11		
33	NAM	401	Manque ± SO	BC1703 ACP	SOURCE SO	X		G1		
34	NAM	401	Manque ± T1 (Principal)	BC1703 ACP	SOURCE T1	X		G1		

Figure 4. Alarm file

4.2 Results and discussions

In this paper, the experiments were performed to juxtapose three well known metaheuristic approaches (SA, GA and PSO). We created a dataset of modeled alarms. Evaluation procedure was done as follows. Initially, the dataset has been divided into two sub-sets, one for training and the other for validation using hold out technique. Then, the training dataset is used to train the Multi-Layer Perceptron (MLP) network.

The multi-layers (MLP) is one of the well-known neural network models. The MLP architecture consists of one input layer, one output layer and one or several hidden layers. In the input layer, no computation is accomplished, unlike the two others layers. A simple MLP network is shown in Figure 5.

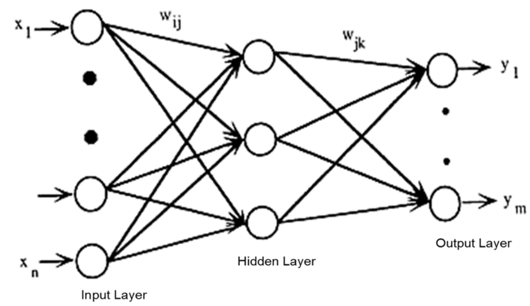


Figure 5. A simple Multi-Layers Perceptron

Back propagation is one of the most widely populated algorithm [41], used for adjusting the MLP's synaptic weights. Mainly, this approach involves two phases (Forward and Backward).

- *Forward phase*:

Each input x is fed into the input layer. Then, from the input layer to the output layer, the neurons' activities are adjusted and a set of output patterns are generated. Next, these output patterns are compared with the target output and the error values are computed.

- *Backward phase*: when the forward phase is accomplished, the network bias and weights are updated using the error values, starting from the output layer to the input layer. This is done in order to reduce the error network.

The algorithm may require many iterations, until a pre-satisfied performance network is reached.

Once the model has been created, a bloc of metaheuristics methods (SA, GA and PSO) for its certain configuration is used to adjust the inferred model. Indeed, MLP-based metaheuristic is applied to configure the parameters (weights) of the MLP neural network using training algorithms based on metaheuristics optimization approaches mono-objective.

In this way, it is hoped that the MLP's performance will be improved. Next, the test dataset is used to check the performance in term of objective function value of the resulting model.

The fitness function could be defined as follows:

$$f_{obj} = \min\ (FPR + FNR) \quad (3)$$

where FPR is the False Positive Rate and FNR is the False Negative Rate.

The experiments were performed in the Matlab environment.

Table 3 presents the obtained computational results performed for each metaheuristic used in such study.

Table 3. Results obtained using different metaheuristics

Experiments	*Metaheuristic*	*Nbr of eval*	*MLP Architect*	E_{learn}	*f value*
# 1	AG	20	[8 13]	45,45	38,10
# 2		100	[10 20]	24,32	14,28
# 3		10	[7 5 10 11]	50,00	0,00
# 4		50	[6 20 15]	52,63	45,45
# 5	SA	100	[20 9]	36,36	7,14
# 6		500	[8 10]	50,00	19,05
# 7		100	[8 15 20]	55,56	35,71
# 8		1200	[30 7 14]	38,46	7,14
# 9	PSO	50	[6 30]	62,22	23,81
# 10		50	[20 7]	27,50	23,08
# 11		100	[10 15 16]	17,50	12,50
# 12		100	[30 6 10]	48,89	25

This table shows the best fitness function founds after a predefined number of the objective function evaluations and different setting for the MLP topology. Please notice that the Elearn colon presents the learning error obtained by the Multi-Layer Perceptron neural network (MLP).

According to this table, it appears that the error rate (fitness function) obtained by the three metaheuristics were more accurate than the training error rate achieved by the standard Multi Layers Perceptron (MLP) technique.

This is due the fact we adjusted more the MLP weight using the chosen metaheuristic that have reached the global (or close) optimal value of the fitness function.

Furthermore, Table 3 shows that the GA achieved the best results with small number of generation. However, SA was less than the GA's fitness function value but yielded solution with optimal architecture setting.

The PSO metaheuristic was slightly worse than the other metaheuristics.

Figure 6 presents a comparison between the accurate classification percentages achieved by the different metaheuristics. The result for the alarm data set confirmed the advantage of GA over PSO and SA metaheuristics.

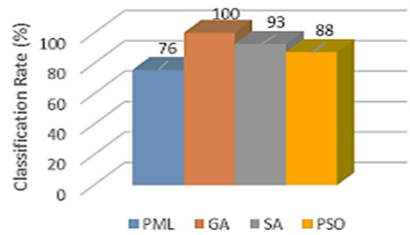
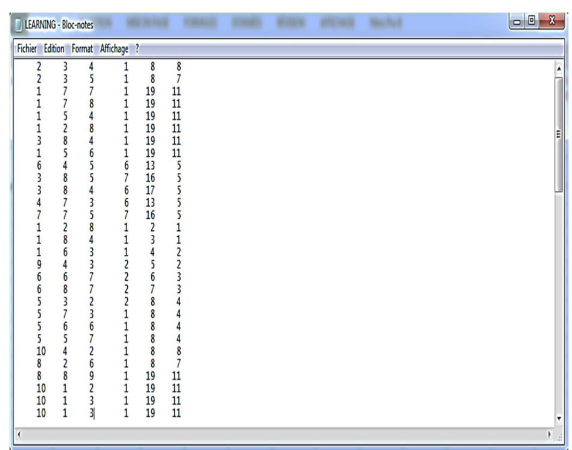


Figure 6. Classification rate of different algorithms

From the simulation results, we believe that metaheuristics based optimization work well in the context of Alarm classification.

In order to capitalize knowledge and enrich the domain ontology. The objective of this activity is store the result generated from learning step.

A resulting GA algorithm is composed of a set of alarm-category to constraints involving independent alarms. The result file of the learning step consists of a set of columns. The first five ones present the characteristic of modeled alarms (Input of Learning system) and the last Colum displays the classification result about different category of alarms see figure 7.



LEARNING - Bloc-notes

Fichier Edition Format Affichage ?

```
2   3   4   1   8   8
2   3   5   1   8   7
1   7   7   1  19  11
1   7   8   1  19  11
1   5   4   1  19  11
1   2   8   1  19  11
3   8   4   1  19  11
1   5   6   1  19  11
6   4   5   6  13   5
3   8   5   7  16   5
3   8   4   6  17   5
4   7   3   6  13   5
7   7   5   7  16   5
1   2   8   1   2   1
1   8   4   1   3   1
1   6   3   1   4   2
9   4   3   2   5   2
6   6   7   2   6   3
6   8   7   2   7   3
5   3   2   2   8   4
5   7   3   1   8   4
5   6   6   1   8   4
5   5   7   1   8   4
10  4   2   1   8   8
8   2   6   1   8   7
8   8   9   1  19  11
10  1   2   1  19  11
10  1   3   1  19  11
10  1   3   1  19  11
```

Figure 7. Example of learning resulting file

The learning system converts the designation of each alarm parameter to a numerical value to do the classifiaction. For example the first line in figure 7, we can interpret that the combination of the values (2, 3, 4, 1, 8) corespending to (alarm source, alarm source equipment, emergency level, date of alarm, failure equipment) that the alarm is part of Alarm class No. 8 corresponding to *Fuse Class*.

To interpret the result generated in the learning phase, the system establishes mapping between alarms, thanks to knowledge base.

Results are then stored as instances of the ontology by using OWL API. This API allows us to establish the link between the new alarm-instance with alarm-category in the knowledge base.

Finally, while instanciated in the ontology, the list of alarm classification can listed (see Figure 10) with the following SPAQL query 1(see Figure 9).

Query

```
PREFIX ns:<http://www.owl-ontologies.com/Ontology1412765787.owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
SELECT ?Alarm ?id_AlarmCategory ?Description_AlarmCategory
WHERE
{
?Alarm    rdf:type ns:Alarm;

          ns:belongTo ?Alarm_Category.
?Alarm_Category      ns:id_AlarmCategory ?id_AlarmCategory;

          ns:Description_AlarmCategory ?Description_AlarmCategory.
}
```

Figure 9. Sparql Query to list alarms classes

Results

Alarm	id_AlarmCategory	Description_AlarmCategory
Alarm_SURCHARGE_THERMIQUE	G9	LIGNE
Alarm_Buchholz__TSA	G10	TSA
Alarm_Anomalie__MAX_I_MT	G5	PROTECTION
Alarm_Régulation_manque_CC	G11	TR
Alarm_Niveau_Haut_TR	G11	TR
Alarm_Défaut_aéroréfrigérant	G11	TR
Alarm_Signalisations_Consignées	G2	ICS
Alarm_Disj_perte_SF6__2_stade	G4	DISJENCTEUR
Alarm_Défaut_commande_disjoncteur	G4	DISJENCTEUR
Alarm_Manque_SO	G1	T1SOURCE
Alarm_Régulation_en_anomalie	G11	TR
Alarm_température__TSA	G11	TR
Alarm_Déclenchement__par__surcharge__thermiq...	G10	TSA
Alarm_Fermeture__Disjoncteur__par_CCN	G8	FUSE
Alarm_Manque_T1	G1	T1SOURCE
Alarm_Protection__différentielle_en_anomalie	G5	PROTECTION

Figure 10. List of alarm classification

5. Conclusions

In a predictive maintenance process, alarm management is a main activity due to the difficulty lies operators to manage the flood of alarms. In order to reduce this problem, the objective of this work is to provide an alarm classification method based on semantic correlation.

In contrast to major studies of the correlated alarms, our work does not take into acount the occurrence delay as correlation factor. Instead we adopting a Knowledge Discovery process and handling the maintenance ontology FOMES, in the aim of including semantic-correlation aspect.

In the learning level of Knowledge discovery process, we have presented a experimental study to compare three metaheuristics algorithm. We applied our appraoch on a concrete use case of Electricity Transmission System. The results shown an efficiency of 100% of classification rate depending on the used GA algorithm.

Future work should pay attention to test the methodology on other datasets, and feature selection methods. We additionally, should improve the robustness of the database and create a complete software for the management of alarm in Electricity Transmission System. Thus, enrich our database and make it available online for a general use by other researchers.

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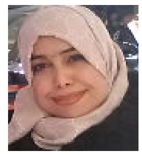
8. Biography



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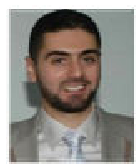

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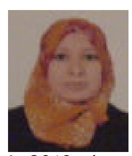

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