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Learning Methods for Distributed Diagnosis: a Failure Classification Methodology in Discrete Event Systems

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Abstract: In the dependability context, diagnosis is fundamental for identifying and classifying failures to reduce system malfunctions and accidents that can cause serious damage to property and people. Currently, systems are generally complex and the distribution approach of diagnostic function makes it possible to better managing systems to be diagnosed. This article proposes a methodology for the distributed diagnosis of Discrete Event Systems, which are dynamic systems widely spread. The proposed approach, based on a generic model, is formed of two sequential steps. The first one consists in the system modeling in order to understand real behavior of the studied system, through a distributed recovery of signals. The second step is to standardize and process data for the classification of failures. To achieve this challenge, two learning classification methods are adopted: the Learning Algorithm for Multivariate Data Analysis (LAMDA) coupled with the K-Nearest Neighbor algorithm (K-NN). The methodology is applied on a particular discrete event system, a railway transport network following a real case of railway line. The obtained results showed improvement of the classification rate by recognition, also becoming better that the supervised classification rate. The adopted methodology offers a distributed diagnosis framework, which emerges as an efficacy and robust way for classify any failures of systems.

Keywords: Dependability, failure, distributed diagnosis, learning methods, classification, LAMDA, K-NN algorithm.

1. INTRODUCTION

The need to ensure dependability [2] of systems and to monitor their actual behavior makes diagnosis an indispensable and fundamental operation. Indeed, slightest dysfunction of the system can generate disasters and it's important to identify failures that cause. The diagnosis aim [33] is to detect probable cause of failure. In this context, many approaches [11,13,24,28] have been developed: these methods are based on a model of the normal and/or failing system behavior. Diagnosis methods differ according to different criteria as process dynamics (discrete, continuous or hybrid), complexity, implementation (on-line and/or off-line), nature of information (qualitative and/or quantitative), depth (structural, functional and/or temporal) and distribution (centralized, decentralized or distributed). The difference can also about localization, external and internal methods [26]. Whatever orientation of methods, it is generally adopted that industrial diagnosis is a deterministic causality relation between the cause and the effect [33].

Knowing that diagnosis becomes very complex when systems to be diagnosed are no longer elementary, integration of the distribution notion becomes an important issue. We are interested in distribution approach of the diagnostic function, especially on Discrete Event Systems (DES). These are dynamic systems allowing modeling and analysis of human-made systems like manufacturing, communication and transportation offering an interdisciplinary view [29]. Given complexity of systems, this work focuses on a model which is an abstract and partial view of the system behavior.

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To exploit potentialities of a DES, physically distributed, authors propose a methodology, on two steps and integrating a generic model. The first step consists in modeling the DES using a method based on logical models. So, simulation of obtained model makes it possible to better understand real behavior of the studied system. The second step is to standardize and process obtained data for classification of failures according in terms of severity. To obtain best classification, the Learning Algorithm for Multivariate Data Analysis (LAMDA) coupled with the K-Nearest Neighbor algorithm (K-NN) is used.

Remainder of the paper is organized as follows: Section 2 presents distributed diagnosis and the two learning methods. In Section 3, complete methodology is described by assembling the two paradigms that represent respectively the fuzzy LAMDA method and the K-NN algorithm. Section 4 consists of methodology application on a particular DES, a rail transport network; system specification and simulation of the distribution modules are given. The proposed classification algorithm is applied in Section 5, thus validating the approach, where comparative and interpretation of the obtained results are discussed.

2. BACKGROUND

The diagnosis function consists of detecting, locating and identify a fault in order to determinate its causes. Identified dysfunctions require corrective actions to regain a normal functioning and to limit consequences of breakdowns that can be catastrophic.

This becomes an important issue when systems to be diagnosed are large and complex. In this case, the criteria dedicated to the distribution and the process are to be considered. Many works focus in this way, like an embedded diagnosis development [4,16], based on three types of architecture (centralized, decentralized and distributed), a centralized diagnostic approach for timed systems and dynamic systems [9]. A diagnosis structure based on decentralized models of a complex system represented by qualitative constraints is proposed in [7]. Authors in [25] work on telecommunications networks which are based on the fact that the system model is very large. Many models-based diagnostic approaches are derived from the DES [8,14,27,28,31].

To be effective, the diagnosis function must rely on the system attitude before and after failures. Therefore, classification of failures is fundamental and often used to view the system behavior [3,19,22]. Following this context, the aim in this work is to classify failures of spatially distributed discrete events systems, helping the operator to limit the number of failures, to identify them and to obtain the best distribution of elements.

Considering that the learning techniques are adequate and widely applied in classification problems, the authors adopt this research framework through the two Learning classification methods, LAMDA and K-NN method. LAMDA method has shown its effectiveness when it comes to classification with multi-source learning based on fuzzy logic. This gives the expert a real perception on the system behavior as well as the state change and it allows better model human reasoning based on uncertainty. K-NN method is used for indistinguishable elements, which are reclassified and a final ranking is obtained.

2.1. LAMDA method

LAMDA method has been used in very diverse fields such as psychology [1], industrial processes [18], selection of sensors [23] and segmentation of biological images [10].

A software SALSA (Situation Assessment uses LAMDA claSsification Analysis) [17–19] allows its implementation. LAMDA approach is a learning technique based on fuzzy logic. The principle of LAMDA methodology is classification of objects, which representing information. Objects are represented by descriptors with standardization of values. Each object is affected to a class through the Marginal Adequacy Degree (MAD) function. This function defines a degree between attribute adequacy to a class and inadequacy of the attribute to this class.

For numeric descriptors, the MAD evaluation can be made through many functions, in particular fuzzy extension of binomial distributions. In this work, the functions [17] Lamda1 and Lamda2 are used:

- Lamda1: $$MAD(x/p) = p^{x}(1-p)^{1-x} , \tag{2.1}$$

where p is the parameter value of the class C which describes the descriptor and x is the normalized value of the descriptor z.

- Lamda2: $$MAD(x/p) = Kp^{x}(1-p)^{1-x} , \tag{2.2}$$

where $K = \dfrac{\log(\frac{p}{1-p})}{2p-1}$.

The normalized value x is given by equation (2.3):

$$x = \frac{z - z_{min}}{z_{max} - z_{min}} , \tag{2.3}$$

where z_{max} and z_{min} are respectively the maximum and minimum values of z.

Next, the Global Adequacy Degree (GAD) is calculated. For an element (described by 1 to d descriptors), the GAD evaluation is obtained by aggregation of all MAD of this element to a class through logic operators like intersection and union functions. So, the linear compensation is done according to the following equation (2.4):

$$GAD_{\alpha}(MAD_1,..., MAD_d) = \alpha\, T(MAD_1,..., MAD_d) + (1\text{-}S)(MAD_1,..., MAD_d) , \tag{2.4}$$

where
- T is the T-Norm connector (intersection),
- S is the T-Conorm connector (union),
- α is the Exigency Index $\in [0,1]$.

An important feature of the LAMDA methodology resides in the taking into account of the information lack for indistinguishable elements and in this case, a Non Informative Class (NIC) is created. The exigency parameter measures affectation of an individual to a class. For $\alpha = 0$, the classification is not exigent and the highest requirement is obtained for $\alpha = 1$. So, increasing the value α implies increasing the number of elements assigned to the NIC [18]. We bring the NIC notion closer to the Residual Class (RC) notion. Indeed, in classification domain, introduction of this particular class allows considering the unclassified elements: objects not belonged to any class are assigned to an additional residual class [32].

The LAMDA method can adapt to a situation evolving over time, so it can handle qualitative and quantitative variables simultaneously by using appropriate marginal adequacy functions.

Despite this property, there is no guarantee to obtain the best partition as results depend on choice of the connectives and the exigency index. To palliate of these disadvantages, the proposed solution in this article is introduction of the well-known K-NN method.

2.2. K-NN method

The K-NN method is the simplest and widely used classifiers [30,32]; it is a powerful tool for any classification study on unknown specification about data distribution. The K-NN method uses two parameters: the number K and the similarity function to compare new case with the already classified cases.

The K-NN method [30] follow three actions: calculate distances to obtain a learning base, sort to have the K smallest and choose the distance which belongs to the majority class.

The similarity function which represents distance between the test sample and the training data samples, is paramount to the correct algorithm functioning. There are several measures of distances, and the most used is Euclidean distance [30], given by equation (2.5):

$$D(X,Y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2}\ , \qquad (2.5)$$

where x_i and y_i represent coordinates of the points X and Y.

3. PROPOSED METHODOLOGY

3.1. The generic model

Centralized approach is not satisfying for design of diagnostic method dedicated to systems having a distributed architecture. So, distribution notion of the diagnosis function becomes essential. In this context, we propose a methodology (Fig. 3.1) based on a generic model, carried out in two modules.

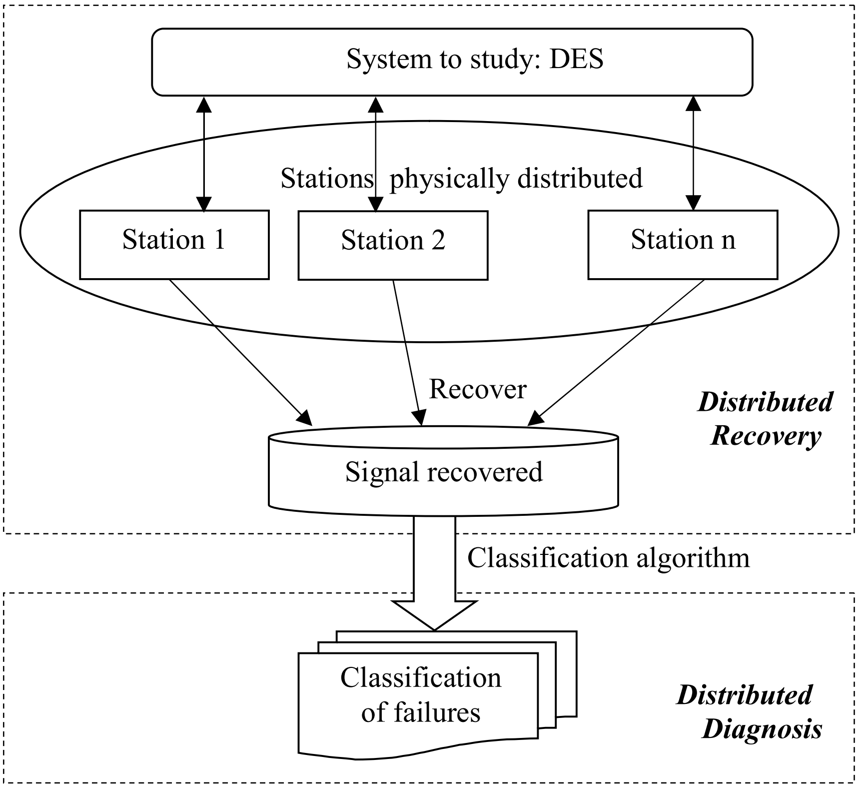


Fig. 3.1. Proposed methodology

The first module involves aim at the distributed recovery of signal and transformation of this signal via intelligent devices, taking into account communication between the physically distributed stations. Highlighting the need to have a model representing different relationships between generated events by the studied system, this generic module relies either on existing systems like SCADA (Supervisory Control and Data Acquisition) system [6, 15] or on systems dedicated to particular domains.

Second module is the main issue of the article; it consists in providing a diagnosis aid based on recovered signal analysis by integrating an improved classification algorithm through two learning paradigms. The first one is based on fuzzy logic and more particularly LAMDA method and the other one uses K-NN method. The aim is giving the operator an orientation to know better the real situation of the system in order to make the right decision concerning a specific failure.

3.2. The classification algorithm

As already mentioned, the proposed classification algorithm involves two principles; the first is the LAMDA method application, giving classified elements and indistinguishable elements affected to a specific class (NIC). These last elements are reclassified using the principle of k nearest neighbors in order to correct the obtained classification.

This article studies influence of the K-NN algorithm integration in the recognition part of the LAMDA method, in particular by the studying non classed elements. These individuals are in the Residual Class which has the same characteristics as the Non Informative Class. Obtained results are compared with the supervised part of the method using same parameters chosen by the operator to have the correct classification.

The general algorithm of classification integrates the following steps for an element X, described by 1 to d descriptors. We included data preprocessing to have normalized values of descriptors.

Complete Classification Algorithm:

Input: A Sequence of elements X / $X = x'_1, x'_2, ..., x'_d$

Step 1: Normalization of each element using equation (2.3) giving X / $X = x_1, x_2, ..., x_d$ such as x_j is a normalized value.

Step 2: For each element X, Calculate the $MAD(x_j/C_k)$ with regard to class C_k using the functions Lamda 1 or Lamda 2 through the equations (2.1) and (2.2).

Step 3: Calculate the $GAD(X/C_k)$ for the element X using the equation (2.4).

Step 4: Select the maximal value of GAD_i.

Step 5: Assignment the element X to the class C_i. If an element has low membership in all existing classes, this element is affected to the NIC.

These steps are issued from the LAMDA method. At the end of the 5th stage, a first ranking is obtained according to different classes and the non informative class. The next steps introduce the K-NN method and let us considering the NIC as Residual Class (RC).

Step 6: Choose a value for K.

Step 7: For each element X of RC, Calculate distance (equation 2.5) between the individual of the RC and these neighbors.

Output: Classification of all elements X.

By application of this methodology, a final ranking is obtained with corrected classes where all elements are classified.

4. METHODOLOGY APPLICATION ON A DES: RAIL TRANSPORT SYSTEM

As an illustration of the proposed generic model, we consider a particular discrete event system, a railway transport network.

This transportation system is considered a safety critical system [30]. So, a management environment of failures is important for increasing dependability and ensuring safety of property and persons.

4.1. Specification of the rail transport system

The railway system comprises two elements closely linked to infrastructure and vehicle: the traffic loads, the type of trains and rolling stock on the track lead to an irregular degradation of the geometry. The speed accelerates this degradation and a reduction in the component life.

A real case is studying through the line Oran (west city of Algeria) to Algiers (the capital city); distance between these two cities is of 422km. A measurement car [21] is used for maintenance and renewal of railways. The vehicle exhibits dynamic behavior to be improved, in particular case when the vehicle passes over geometrical defects on the track or on switches. The measuring car is intended to detect and record geometrical parameters of the track, mainly by intervening urgently to ensure safety of the train movements through checking types of faults [5, 12]. The controls concern:

- The longitudinal leveling of 2 lines of rail.
- The cant values.
- The left, which represents the torsion of the track.
- The defect of dressage.
- The variation of the spacing.

The major disadvantages of the measurement car are on the one hand inability of the car to interrupt monitoring and diagnosis, and on the other hand the high probability (75%) of having a false registration if the sensors do not work. Furthermore, as it is a towed car without motor, this can cause a delay of the train with no information distribution.

4.2. Distribution of the Recovery Phase between Communicating Modules

A solution is proposed to delimit the disadvantages generated by the measuring car: the rail transport system has a control center and physically distributed stations, through Remote Terminal Units (RTU). For the considered line (Fig. 4.1), the command center is located at the Algiers level; departure will start from Oran (Kilometer Point 0) which sets post1, Relizane (Kilometer Point 1) is workstation2 and Ain Defla (Kilometer Point 2) is post3.

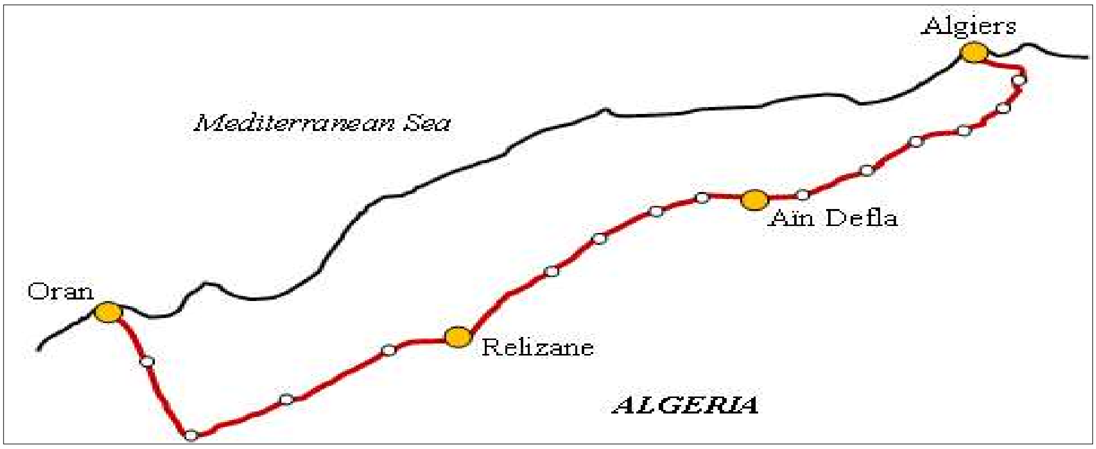


Fig. 4.1. The railway line with RTUs

Each station has cells except workstation1 (departure) and control center (arrival); this one has circuit breakers which can be either the data logger or protection. The data logger contains various measures such as train speed, size and time; the protection contains defects (Spacing, Left, long profile, Vertical alignment, high and down points, Devers, arrow).

Graphical data (Fig. 4.2) between kilometer points 1 and 2 are recovered by RTUs, giving simulation of the two defects, Spacing (S) and Left (L). This result is sent to the command center.

Control station and other stations are connected to a telecommunication network via a transport medium using standard protocols. A database allows storage of failures, as:

- TS: Tele Signalization (simple or double) which represents defects and the track state.
- TR: Tele Regulation that represents target speed for modification of parameters.
- TM: Tele Measure for controlled measurements to monitor current speed of the train.

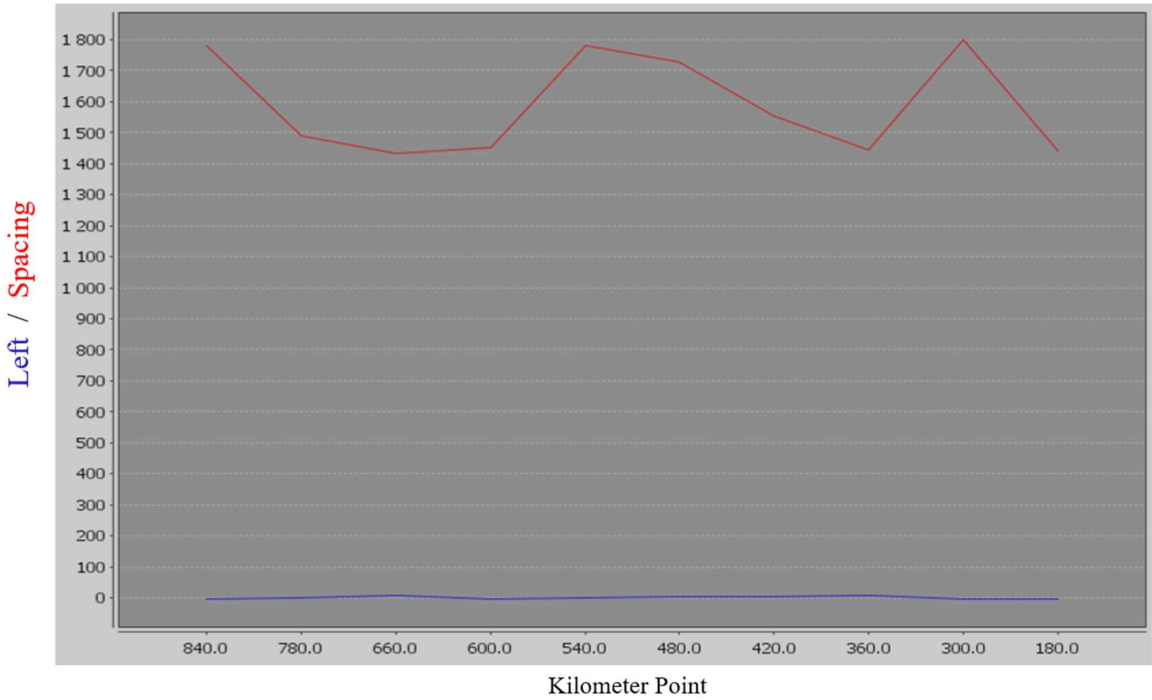


Fig. 4.2. Graphical data for simulation of two defects

5. APPLICATION OF THE PROPOSED ALGORITHM

The following section illustrates in detail the methodology through application of the proposed algorithm on a set of individuals recovered from a distributed architecture; at first, LAMDA method is applied followed by K-NN method. The obtained results show the classification improvement in using same parameters

Thereby, the operator will carry out a multidisciplinary analysis on the collected data, so that he can make the right decision in real time regarding maintenance during the failure occurrence. He also manages a new failure that can belong to a class already predefined, by using the adopted classification and notes its influence to the given results in the case where learning is supervised.

5.1 Classification obtained by LAMDA

5.1.1. Specification of descriptors

Consider a sample of 23 individuals collected from intelligent equipments installed on railway transport network, in the Oran-Algiers line. We wish classifying these elements in supervised learning mode.

Descriptors are quantitative type, representing respectively the left and the spacing. In agreement with the expert and following defined measurement values, two classes are identified: the first represents right track and the second represents wrong track.

Table 5.1 shows initial values retrieved from RTUs with the two defined descriptors for the 23 elements; each individual is stored with an affectation to the reference class it belongs.

Table 5.1. Initial values of the descriptors

Individual	Descriptors		Reference Class
	Left (L)	Spacing (S)	
1	9.900	1435.00	2
2	16.200	1400.00	2
3	-9.300	1430.00	2
4	14.400	1420.90	2
5	-12.300	1400.00	2

6	1.500	1435.500	1
7	-9.300	1200.00	2
8	12.600	1435.00	2
9	8.600	1435.00	1
10	5.00	1435.00	1
11	-10.800	1600.00	2
12	9.900	1435.00	2
13	2.300	1435.00	1
14	9.300	1700.00	2
15	9.600	1820.00	2
16	15.900	1400.000	2
17	9.100	1400.00	2
18	8.00	1435.00	1
19	3.300	1435.00	1
20	15.300	2000.00	2
21	19.200	2152.00	2
22	13.200	1435.00	2
23	5.400	1435.00	1

5.1.2. Implementation of the LAMDA method

The proposed algorithm is applied on data and the first steps concern LAMDA method. However, as initial values are evaluated on different scales, it is necessary to define a context which groups normalized values of descriptors. This data translation is supported in step 1 of the algorithm. The normalization (equation 2.3) allows values to always be in the interval [0,1] and following figure (Fig. 5.1) presents description of context obtained with the new values normalized for the two descriptors.

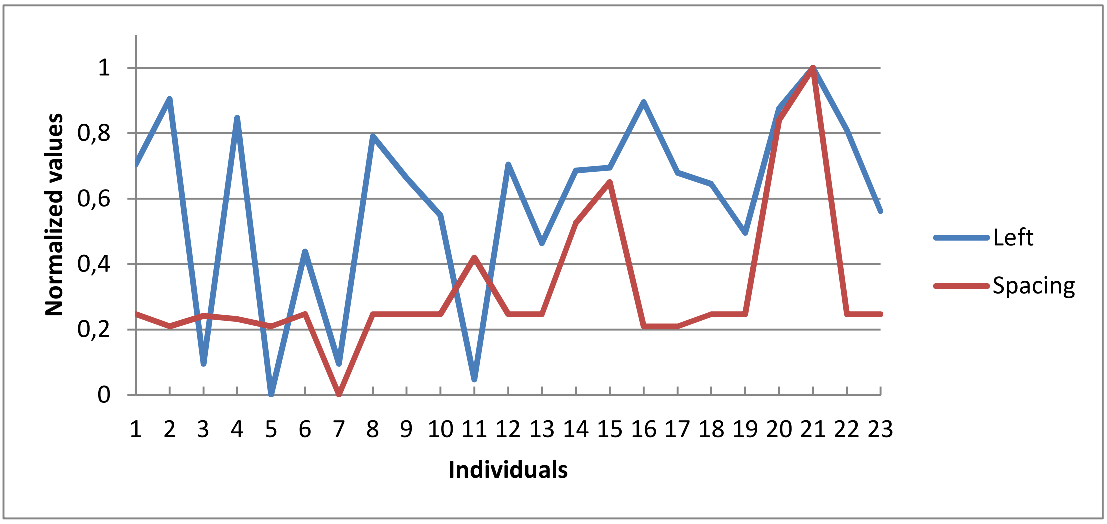


Fig. 5.1. Description of the context

Two types of classification (supervised and recognition) can be used in LAMDA method implementation. In this context, a classification rate (Table 5.2) can be obtained by varying the three parameters: the first one is exigency index α, getting values in [0,1].

After simulation, we retain the extreme values as well as two intermediate values. The second parameter are the connectives and we used the two most known family (probabilistic and the minimum-maximum) for T-Norm and T-Conorm values. The last parameter are the two functions Lamda1 and Lamda2 given by following equations (2.1) and (2.2), specified previously.

Table 5.2. Learning and recognition rate corresponds to two types of classification

α values	Connectives	Functions	Supervised classification: Rate of learning and recognition	Classification by recognition: Rate of learning and recognition
0	Probab	Lamda1	69.56 %	56.52 % class NIC {11,15,20}
		Lamda 2	47.82 %	34.78 % class NIC {11,15,20,21}
	MinMax	Lamda1	52.17 %	52.17 %
		Lamda 2	47.82 %	47.82 %
0.3	Probab	Lamda1	73.91 %	52.17 % class NIC {11,15,20,21}
		Lamda 2	47.82 %	34.78 % class NIC {11,15,20,21}
	MinMax	Lamda1	69.56 %	47.82 % class CR{11}
		Lamda 2	47.82 %	47.82 % class CR {11}
0.7	Probab	Lamda1	73.91 %	52.17 % class NIC {11,15,20,21}
		Lamda 2	47.82 %	34.72 % class NIC {11,15,20,21}
	MinMax	Lamda1	73.91 %	60.86 %
		Lamda 2	73.91 %	39.13 % class NIC {11,15,20,21}
1	Probab	Lamda1	73.91 %	56.52 % class NIC {11,15,20,21}
		Lamda 2	43.47 %	34.78 % class NIC {11,15,20,21}
	MinMax	Lamda1	65.21 %	43.47 % class NIC {3,5,6,7,11, 13,14,15,19,20,21}
		Lamda 2	65.21 %	34.78 % class NIC {3,5,6,7,11, 13,14,15,19,20,21}

From the table, difference between the two classification modes is appearance of the Non-Informative Class (NIC) in recognition classification. In this case, to improve the rate keeping same parameters, next steps of the proposed algorithm are applied. It consists in K-NN method implementation on elements belonging to Residual Class (RC), which has the same characteristics that the NIC.

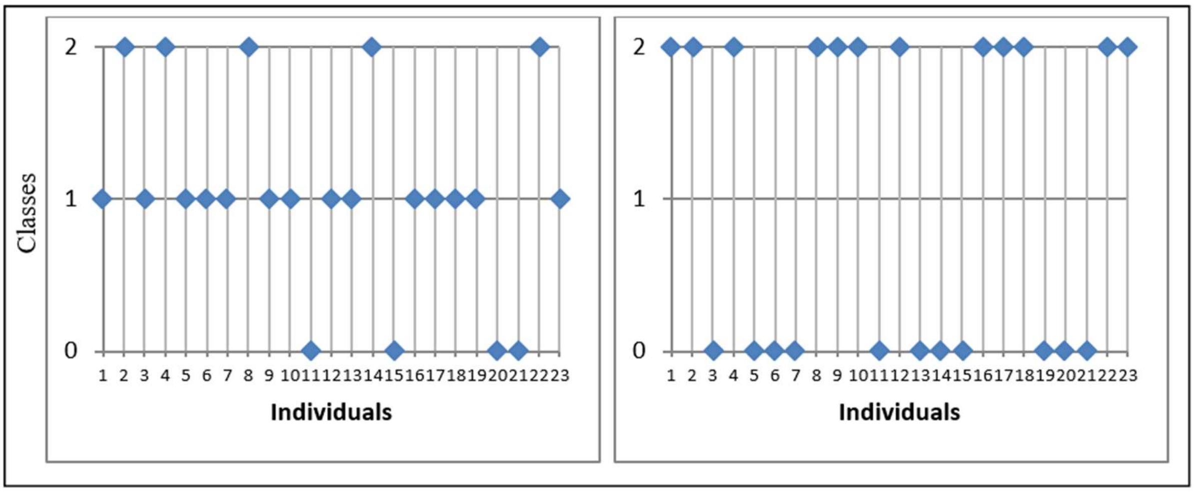
So, individuals already classified in the NIC are ranking again by adopting set of last steps of the classification algorithm. Final results will be compared with results whose learning is supervised while preserving same parameters predefined by the expert.

5.2. Application of the K-NN method

5.2.1. Identification of residual class

Let us take the classification obtained by recognition and two cases can appear following two or three classes, with the RC identification (class 0). For example, look at following two cases (Fig. 5.2, a and b) defined with specific values for the three parameters (exigency index α, connectives and functions).

The first case (parameters: 0.3, Probab, Lamda1) gives the presence of three classes: class 1 is {1,3,5-7,9,10,12,13,16-19,23}, class 2 is {2,4,8,14,22} and {11,15,20,21} for RC. The second one (parameters: 1, MinMax, Lamda2) deals with two classes: {1,2,4,8-10,12, 16-18,22,23} for class 2 and {3,5-7,11,13-15, 19-21} for RC.



a. case 1 **b.** case 2

Fig. 5.2. Identification of residual class

Consider the highest value for exigency index, which is located in the case 2; in this case, recognition rate is 65.21% in supervised classification mode. With same parameters, in classification by recognition the rate is 34.78% with the appearance of RC giving unrecognized individuals. These elements are reclassifying by application of the two last steps of the proposed algorithm through classifier K-NN, in order to improve classification rate by recognition.

5.2.2. Reclassification of the 6th individual

For illustration, we apply the method on one element of RC, the 6th individual. Values of the two descriptors L and S are respectively 1.500 and 1435.500; this element has three neighbors (K=3): the 4th, 8th and 9th individual. Following the reference classification, the 9th belongs to class 1 and the two others elements belong to class 2. So, Euclidean distance between this 6th individual and his neighbors is calculated (Table 5.3), by application of equation (2.5) defined previously.

Table 5.3. Calculation for the reclassification of the 6th individual

Neighbors	Class	Descriptors (L _ S)	Distance
4	2	(14.4_1420.9)	19.48
8	2	(12.6_1435)	11.11
9	1	(8.6_ 1435)	7.11

This element belongs to class which has the lower evaluated distance compared to other neighbors. Hence, the 6th individual belongs to class 1 as its distance is the smallest from all calculated distances.

5.2.3. Reclassification of all elements

Same approach is applied on full elements of RC; Table 5.4 summarizes the classification decision for all other individuals after algorithm execution.

Table 5.4. Reclassification of RC elements

Individual	K	Neighbors	Class	Distance	Decision
3	2	2	2	39.37	Individual 3 belongs to class 2
		4	2	11.12	
5	2	4	2	33.36	Individual 5 belongs to class 2
		8	2	49.95	
7	2	4	2	222.16	Individual 7 belongs to class 2
		8	2	236.01	
11	2	10	1	165.75	Individual 11 belongs to class 2
		12	2	165.06	
13	3	10	1	2.7	

		12	2	7.6	belongs to class 1
		16	2	37.54	
14	2	12	2	265	Individual 14 belongs to class 2
		16	2	300	
15	2	12	2	385	Individual 15 belongs to class 2
		16	2	420	
19	2	18	1	4.7	Individual 19 belongs to class 1
		22	2	9.9	
20	2	18	1	565.04	Individual 20 belongs to class 2
		22	2	565.00	
21	2	18	1	717.08	Individual 21 belongs to class 2
		22	2	717.02	

5.3. Results and discussion

According the above table, final results are illustrated in next figure (Fig. 5.3).

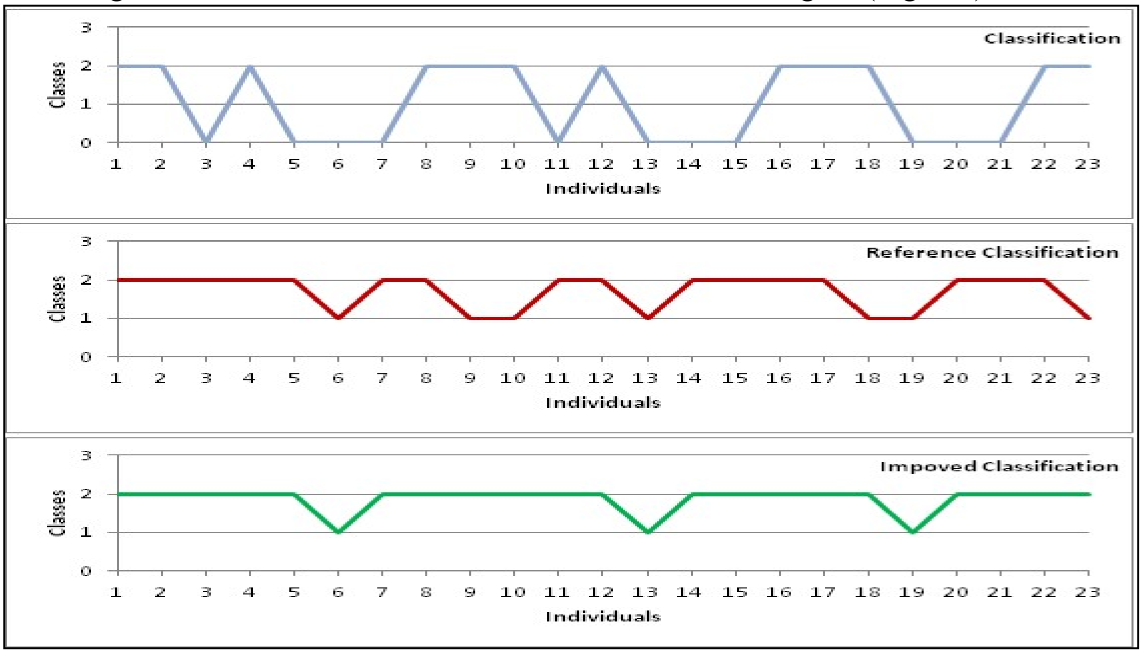


Fig. 5.3. Evolution of the classification

Interpretation of different graphs shows classification evolution: all individuals belonging to the RC are classified. Compared to reference classification, ranking of some elements did not move while others were refined

On this sample of individuals, the rate of learning and recognition is calculated again, giving an improved rate (Fig. 5.4) from 34.78% to 82.60% with a growth of 47.82%.

Using function Lamda 1 and with same parameters (exigency value equal to 1 and the connective MinMax), an improvement in the rate is also found (Fig. 5.4), from 43.47% to 78.26% with an increase of 34.79%. Note that supervised classification rate is 65.21% with same parameters and the rate classification by recognition that was lower is now better.

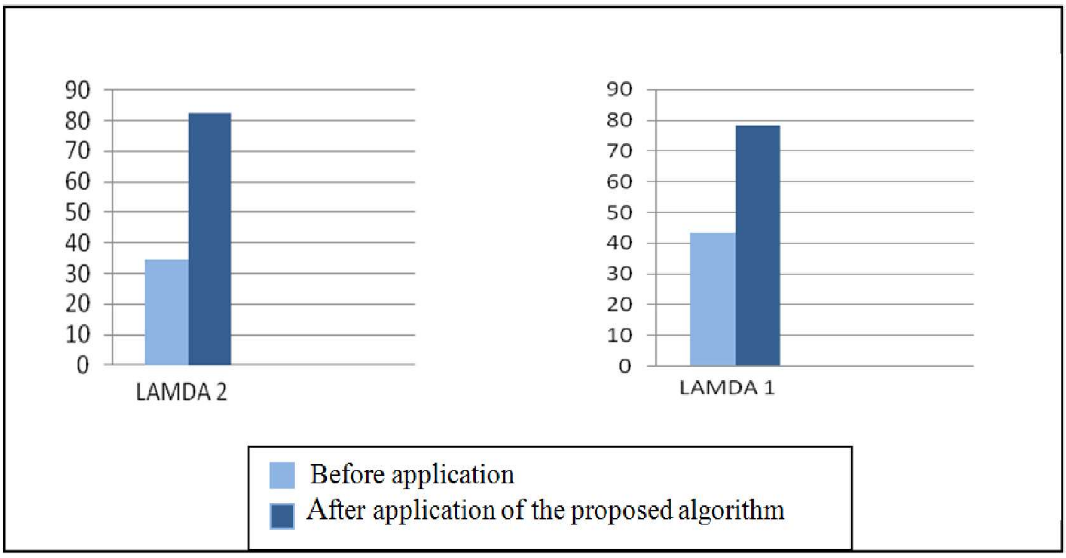


Fig. 5.4. Improvement of the classification rate

6. CONCLUSION

Diagnosis is fundamental to master failures of systems in order to protect human lives, particularly in specific systems such as rail networks.

This article is focused on this framework, by proposing a methodology around a distributed approach of the diagnosis function for these complex discrete event systems. The approach includes two parts, a distributed recovery of signal and processing part with a classification algorithm. Aim is to facilitate operator task in the decision-making phase about diagnosis. In this context, we proposed an algorithm for classification of failures, based first on the fuzzy LAMDA method, giving ranking results with unrecognized individuals, assigned to the non informative class. Considering this particular class as the residual class, the K-Nearest Neighbor method is then introduced to reclassify unranked elements.

The methodology has been applied to a real case study, which is a railway line. Physically distributed stations are used to collect information and on recovered elements, the proposed algorithm is implemented. Following the two types of classification, supervised and by recognition, ranking of individuals are provided with a classification rate. Results of simulation show that the proposed approach gives an improvement of the classification rate by recognition. Moreover, this rate becomes better that the supervised classification rate.

Future work will aim two main ways, design and application of the methodology. Thereby, in order to perfect the approach, several perspectives can be considered in particular concerning the unrecognized elements by LAMDA method. In this work, Euclidean distance for K-NN approach has been used and other metrics could be studied. More, additional methods from artificial intelligence might be taken up to reclassify these elements.

Furthermore, the presented approach can also be applied to other DES and currently, the generic methodology is being studied on a system of electricity distribution. The real considered system has a control center and substations physically distributed; digital signal is recovered by a SCADA system. The algorithm implementation, based on the two learning methods, is in progress. So, by using the full methodology on different systems, the proposed distributed diagnostic framework, in a dependability scheme, emerges as an efficacy and robust way for classify any failures, while helping in decision making of an operator.

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