Evidential Network for Multi-Sensor Fusion in an Uncertain Environment

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Abstract—Interpreting and quantifying the confidence granted to signals transmitted and received in a sensor network is likely to be called into question by various factors. On an architectural plan, first of all, the nature of the networks or the distance between sensors can induce risk of false alarm or non-detection by misinterpretation of the analyzed signals. External factors related to stresses induced by the environment are also potential sources of measurement errors. Finally, despite the maturity of techniques, internal influence factors related to the accuracy or reliability sensors may also, at a more basic level, impact the confidence placed in the test or the performed diagnosis. A system-embedded intelligence is then necessary to compare the information received for the purpose of decision aiding based on margin of errors converted in confidence intervals. In this paper, we present three complementary approaches to quantify the interpretation of signals exchanged in a network of sensors in the presence of uncertainty.

Keywords: Sensor networks; Uncertainty; Bayesian techniques; Belief functions; Evidential networks.

I. INTRODUCTION

Within the field of science and engineering, data imperfection requires the use of tools to define mechanisms for reasoning with partial knowledge and uncertain information. In [1], several types of imperfections are discerned:

- Incompleteness and vagueness are used to qualify the status of a data. It is said to be incomplete if it is impossible for the source to provide information regarding all or part of the aspects of a problem. Vagueness is a form of incompleteness for when the source provides an imprecise data, the resulting information is necessarily incomplete.
- Uncertainty applies when the source is unable to distinguish the veracity of a piece of information (that is to say whether the information is true or false). It therefore characterizes the extent of information compliance compared to reality. It is possible to distinguish two kinds of uncertainty. Random uncertainty is induced by the variability of an entity in a population and is the outcome of random experiments. This type of uncertainty cannot be reduced since it is the result of chance. Epistemic uncertainty is due to the lack of knowledge and therefore relates to the concept of incompleteness.
- Ambiguity represents the fact that a same information can have several interpretations. It is therefore linked to the formalism of information representation which is not always clear and shared by all the stakeholders. This type of imperfection is very common and is often a source of misinterpretation. It can be avoided when formalizing the representation.
- Granularity of information characterizes the difficulties that appear when two very close values have to be distinguished.

A decision requires integrating this imperfection to justify the actions that will be undertaken. In the field of sensor networks, decisions must be taken at every moment with respect to signals individually emitted by each sensor or regarding the signals received and compiled by a centralized basis. Taking into account imperfect data allows the decision maker to legitimate its choices since he will have at its disposal additional knowledge associating the data with an interval of confidence and a margin of error.

In the following are presented two distinct approaches based on Bayesian Networks (Section II) and Belief Functions (Section III) for integrating and propagating imperfect data in a network of sensors. In Section IV, it is shown how both techniques can be combined and reinforced each other within the same tool, namely evidential networks. Finally, in Section V, a comparative view of the different techniques is presented to show their respective conditions of use.

II. BAYESIAN NETWORK APPROACH

Bayesian Networks are graphic models designed to formalize knowledge with the purpose of reasoning about a problem.

A. Principles

Bayes theorem is central in the mechanism of inference in Bayesian Networks. It makes the link between a series of hypotheses, characterized by probabilities of occurrence, and a series of observations representing the actual state of the system. From the Bayes theorem, it is possible to implement two types of reasoning:

- Diagnosis, or reasoning by backward inference, which allows, in the set of assumptions made, the identification of the probable cause of a given result,
- Prognosis, or reasoning by forward inference, which enables the estimation of the occurrence probability of an evidence with respect to the formulated assumptions.

From a mathematical point of view, the space of hypothesis $\Theta = \{\theta_1, \ldots, \theta_i, \ldots\}$ and observations $\Omega = \{\omega_1, \ldots, \omega_k, \ldots\}$ are defined. To represent the link between observations and assumptions, the probability theory allows the use of a conditional probability distribution based on each verified hypothesis. This distribution can be noted $P^{\Omega}(.|\theta_i)$.

Whether there is a knowledge regarding the values of the hypothesis $\theta_i \in \Theta$, it is then represented in the form of a conditional probability distribution across the observation Ω, noted $P^{\Omega}(\omega_k|\theta_i)$, which characterizes the likelihood of observation ω_k knowing hypothesis θ_i. Bayes theorem can then be used to provide a reasoning forward inference to determine the most probable cause associated with this evidence by calculating the a posteriori probability distribution $P^{\Theta}(.|\omega_k)$.

$$P(\theta_i|\omega_k) = \frac{P(\theta_i) \times P(\omega_k|\theta_i)}{\sum_{\theta_i \in \Theta} P(\theta_i) \times P(\omega_k|\theta_i)} \quad (1)$$

When the probability distribution $P(.|\theta_i)$ is known (i.e., the probability of occurrence of an observation given each hypothesis) and a hypothesis $P(\theta_i)$ is assumed, Bayes theorem allows the implementation of reasoning backward inference to estimate the effect of a hypothesis on an evidence $P(\omega_k)$. By calculating the probability distribution on the evidence it is then possible to predict the most likely one:

$$P(\omega_k) = \sum_{\theta_i \in \Theta} P(\theta_i) \times P(\omega_k|\theta_i) \quad (2)$$

Bayesian Networks are used to formalize knowledge in the form of a causal graph associated with a probability space. They are acyclic directed graphs where knowledge is represented by variables. Each node of the graph corresponds to a variable and arcs represent the probabilistic dependencies between these variables. Formally, a Bayesian network is defined by [2]:

- a graph-oriented without circuit, noted $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, with $\mathcal{V}$, the set of nodes of $\mathcal{G}$, and $\mathcal{E}$, the set of arcs of $\mathcal{G}$,
- a finite probability space $(\Omega, \mathcal{A}, \mathcal{P})$, where Ω is the universe, i.e., the set of all the elements considered in the problem, $\mathcal{A}$ is a σ-algebra on Ω and $\mathcal{P}$ is a measure on Ω such that $\mathcal{P}(\Omega) = 1$,
- a set of random variables defined on $(\Omega, \mathcal{A}, \mathcal{P})$, corresponding to each node of the graph, such that the set of probabilities associated with these variables defines the distribution of probabilities attached to the network:

$$\mathcal{P}(\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_n) = \prod_{i=1}^{n} \mathcal{P}(\mathcal{V}_i | pa(\mathcal{V}_i)) \quad (3)$$

with $pa(\mathcal{V}_i)$, the parent set (also called predecessors or causes) of $\mathcal{V}_i$ in graph $\mathcal{G}$. There are two types of probability tables in Bayesian Networks [2]. Tables of prior probabilities (table II.2) characterizes the chances that the variable $\mathcal{V}_a$ without any parent is in state a_i. Tables of conditional probabilities (table II.2) establish the chances that a variable $\mathcal{V}_b$ is in state b_j based on the state of his parents.

Inference in a Bayesian network consists in propagating information in the network. Indeed, a model using this formalism is generally not intended to be a static representation of knowledge. Beyond the a priori reasoning, evidences may be introduced to update the observed situation and to insert into the model the changes enabling the refinement of the results [3]. This new knowledge, takes the form of a so-called elementary information, denoted $\mathcal{I}$, relative to a particular node. There are two types of basic information. The deterministic information allows instantiating a variable, which is affecting it a precise value, (i.e., $\mathcal{P}(\mathcal{V}_a = a_1|\mathcal{I}) = 1$). The imprecise information modifies the distribution of probability of the variable, either by excluding a value of the universe of the variable ($\mathcal{P}(\mathcal{V}_a = a_1|\mathcal{I}) = 0$) or, more usually, by changing the law ($\mathcal{P}(\mathcal{V}_a = a_1|\mathcal{I}) \neq \mathcal{P}(\mathcal{V}_a = a_1)$).

B. Case Study

The growing need of wiring in avionics, automotive, telecommunications, nuclear plants, buildings, etc., has caused the increase of cable length moving from 200m up to 4km in a modern car. The type of a cable (coaxial, twisted pair, optic fiber, etc.) depends on the nature of the propagating signal (data and energy) into network, the corresponding voltage level and the environment (noise, temperature, vibration, etc.) in which the cable is implemented. One day or another, a cable will show signs of damage involving the appearance of faults (short and open circuit, aging, etc.). These faults can be a consequence of environmental stress (heat, moisture, chafes, etc.) and a cause of dramatic mishaps such as TWA flight 800 in 1996. Therefore, a wiring diagnosis system is needed to detect and locate faults as early as possible. Reflectometry is a suitable diagnosis technique as it requires a single access point to inject a test signal into the cable network. During its propagation, a part of its energy is reflected back to the access point at each impedance discontinuity (fault, junction, etc.). Then, the analysis of the reflected signals, commonly called "Reflectogram", permits to characterize this discontinuity. In the literature, several reflectometry methods are proposed depending on the studied domain and the type of the used test signal [4]. Although standard reflectometry has proven its efficiency in wire fault detection, it suffers from ambiguity problems related to fault location in branched networks. As a solution, a distributed diagnosis strategy is proposed [5].

It consists in using multiple diagnosis systems, called "reflectometer", to make reflectometry measurements at many extremities of the cable network. Here, the major problematic involves the diagnosis system reliability, number and location, signal processing, resource allocation, communication protocol, etc. Based on the uncertainty regarding diagnosis system failure, measurement precision and fault location, the use of Bayesian networks is motivated by the combination of deterministic and stochastic behaviors of such systems of diagnosis [4].

Figure 2 shows the computed reflectogram for the branched network of Figure 1 with an open circuit fault at a distance of 25m from the injection point. Only one reflectometer is placed at the extremity of L1 to diagnose the whole network. The reflectometer and the network are

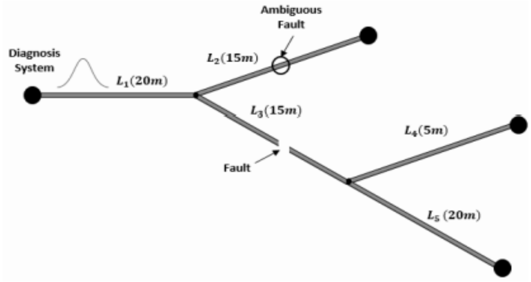

Figure 1: Fault location ambiguity in a branched network

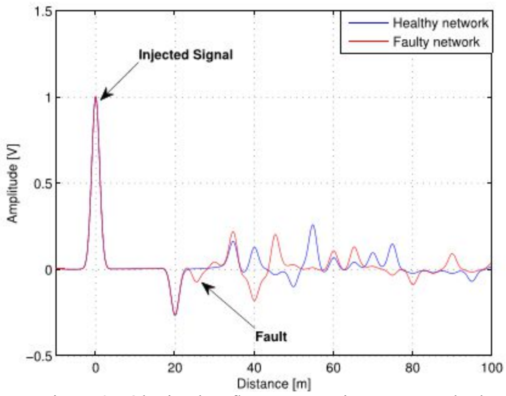

Figure 2 : Obtained Reflectogram using TDR method

considered unmatched, explaining the first positive peak on the reflectogram. The end of lines are also unmatched. Here, the detected fault on L3 cannot be distinguished from the same fault on L2. It is then possible to add another reflectometer at the end of line L. Although, the ambiguity problem is resolved for the fault on branch L, it remains inevitable if another fault appears on the branch L. So, another reflectometer should be added to overcome this ambiguity, which increases the diagnosis cost (number of reflectometers) [6]. As a solution, we proposed to introduce the cable life profile aiming to cancel the fault location ambiguity problem with a low cost. Considering the uncertainty regarding faults location, measurement precision and reflectometer reliability, the use of Bayesian Networks appeared to be appropriate to combine these deterministic and stochastic behaviors [7].

The proposed strategy includes two steps: (1) local diagnosis based on BNs, (2) global diagnosis for the whole network to locate the detected fault(s) [8]. In local diagnosis, each reflectometer introduces the cable life profile to calculate the conditional probability of the presence of the fault on each branch. Then, the obtained results for each reflectometer are integrated into a global BN to locate the fault in the whole network. Simulation results prove the efficiency of the proposed strategy to cancel or mitigate the ambiguity for fault location in a branched network with respect to the reflectometer reliability.

Since this is not the main purpose of the paper, please refer to [6] for more details on the procedures.

III. TRANSFERABLE BELIEF MODEL APPROACH

Based on the work of Dempster [9] generalizing the theory of probabilities by using probability intervals, the belief function theory was developed by Shafer [10] to provide a general framework for the representation of uncertainties.

A. Principles

This combined approach is commonly referred to as the Dempster-Shafer Theory (DST). It is used to represent information based on the belief or the state of knowledge of an entity (person, sensor, etc.) and provides a very rich mathematical framework for:

- the characterization of partial knowledge (including total ignorance)
- the fusion of information from various homogeneous or heterogeneous sources
- the modelling of uncertainty (random and epistemic) related to the state of a system
- the assessment of the degree of confidence associated with a result

The theory of belief is particularly well suited to the representation of different forms of uncertainty. It allows the modelling of problems where the lack of information prevents the reasonable use of probability theory. Belief techniques are used in many fields (decision, data analysis, classification, diagnosis, multi-sensor perception, image processing, etc.) for the very varied tasks such as pattern recognition, likelihood analysis or information merging.

This formalism evolved and saw the emergence of a second approach, developed by Smets in [11]. This approach, called Transferable Belief Model (TBM) is a subjectivist interpretation of the theory of belief functions and allows the analyst to overcome the notion of probability. The TBM approach introduces a decision-making level (also called pignistic level) that irreversibly transforms beliefs (non-probabilistic expression) in a probability-based consistent form to facilitate decision making.

The TBM approach enables the representation of imperfect knowledge from multiple sources [11]. It is based on the assumption that reasoning in uncertainty (credal level) and decision-making (pignistic level) are two cognitive tasks of different kinds:

- The credal level corresponds to the representation and manipulation of the belief statements (without using for example equiprobable distribution.
- The pignistic level makes possible the decision-making by transforming the subjective measures of non-probabilistic beliefs into a measure of probability. This transformation which allows the consideration of risk or bet notions, intervenes only at the time of the decision-making and does not alter the credal level.

Modelling a problem using belief functions, requires to determine the value of the variable ω, which represents the system states. The frame of discernment (FoD) represents all possible n values (or hypothesis) for the variable ω and is denoted by Ω.

$$\Omega = \{\omega_1, \omega_2, \dots, \omega_i, \dots, \omega_n\} = \cup_{i=1}^{i=n}\{\omega_i\} \quad (4)$$

The definition of the belief mass function, denoted m^{Ω}, allows the translation of an observation provided by an agent on the power set of Ω (denoted 2^{Ω}). The power set corresponds to all the subsets that can be formed from the assumptions and the unions of assumptions of Ω. Consequently, the belief mass function is defined as:

$$\begin{array}{rcl} m^{\Omega}: 2^{\Omega} & \rightarrow & [0,1] \\ A & \mapsto & m^{\Omega}(A) \end{array} \quad (5)$$
$$with\ 2^{\Omega} = \{\emptyset, \{\omega_1\}, \{\omega_2\}, \{\omega_1, \omega_2\}, \{\omega_3\}, \{\omega_1, \omega_3\}, \{\omega_2, \omega_3\}, \dots, \{\omega_1, \dots, \omega_n\}\}$$

Notation $m_S^{\Omega}(A)$ stands for the identification of a source S which provides information on proposal A. The basic belief assignment (bba) is the set of belief masses on the proposition $A \subseteq \Omega$ that satisfies:

$$\sum_{A \subseteq \Omega} m_S^{\Omega}(A) = 1 \quad (6)$$

A bba can be transformed to highlight information and to improve the dynamic aspects of TBM, including the fusion rules. The credibility measure or belief (denoted $bel^{\Omega}(A)$) symbolizes the minimal belief in a hypothesis A. It is the part of belief specifically attributed to A (without the part corresponding to the empty set). The plausibility measure (denoted $Pl^{\Omega}(A)$) represents the maximal belief in a hypothesis A. It is the sum of all the masses for A. Both measures are defined as:

$$bel^{\Omega}(A) = \sum_{\emptyset \neq B \subseteq A} m^{\Omega}(B), \forall A \subseteq \Omega \quad (7)$$

$$Pl^{\Omega}(A) = \sum_{B \cap A \neq \emptyset} m^{\Omega}(B), \forall A \subseteq \Omega \quad (8)$$

The transformation from credal level to pignistic level is called pignistic transformation [11]. This non-reversible transformation aims to reduce the bba in a probability distribution so as to be compatible with decision theory. Hence, the mass of proposal A is distributed using equiprobability on the singletons of the FoD, Ω, i.e., on the hypotheses related to A. Therefore, this probability distribution, denoted BetP, can be obtained as:

$$\begin{array}{rcl} BetP\{m^{\Omega}\}: \ \Omega & \longrightarrow & [0,1] \\ \omega_i & \longmapsto & BetP\{m^{\Omega}\}(\omega_i) \end{array} \quad (9)$$

With regard to decision-making itself, it is to select the singleton ω_i of the FoD Ω having the highest pignistic probability to maximize the chances that the hypothesis symbolized by ω_i represents the actual state of the system (or the smallest, if for instance, the goal is to minimize the probability of occurrence of an event). It is therefore to maximize the expected utility in order to rationalize the decision. From a mathematical standpoint, this decision can be expressed by:

$$\omega = \begin{vmatrix} argmin \\ argmax \end{vmatrix} BetP\{m^{\Omega}\}(\omega_i) \quad (10)$$

B. Case Study

An example of an illustration of the concept of belief functions applied to sensor networks can be found in [12]. The author of the work deals with the area of Wireless Sensor Networks (WSN) based especially on infrared or ultrasonic techniques. These networks are made up of smaller equipment whose number varies from hundreds to hundreds of thousands. They can be deployed on one or more locations to observe a particular phenomenon and their mutual collaboration enables the triggering of alerts or the gathering of information on a supervised phenomenon.

The number and the position of the sensors deployed in an area of interest, determine the topology of the network and characterizes its intrinsic properties in terms of coverage, connectivity, cost and life. Therefore, the performance of the WSN depends mainly on the method used in the deployment of sensors. The network architecture is intimately linked to the reliability of the information transmitted by the sensors which determines the quality of network coverage. The belief functions are used in this work to analyze the problem of management of imperfections related to the uncertainty in the data gathering process.

The construction of evidence is based on two states required to specify whether a space point $p \in RoI$ is covered (θ_1) or uncovered (θ_0). Thus, the FoD is the set $\Theta = \{\theta_0, \theta_1\}$. Let s be a sensor, R_s be its sensing range and R_u be a distance ($0 \leq R_u \leq R_s$) (Figure 3).

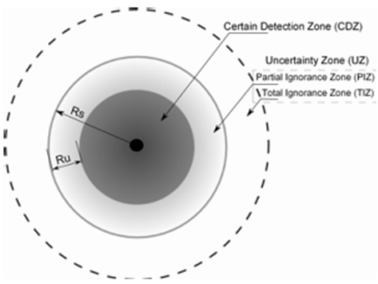

Figure 3: Sensor sensing range representation

Each sensor s provides information on the coverage of a space point $p \in RoI$ (Region of Interest) with a belief $b_{s/p}$. The complementary information $1 - b_{s/p}$ is assigned to the whole FoD because it encodes the sensor ignorance. The output from the sensor s about a space point $p \in RoI$ can thus be represented as a bba $m_{s/p}$ with two focal sets: the singleton $\{\theta_1\}$ and the FoD Θ.

$$\begin{array}{c} m_{s/p}(\{\theta_1\}) = b_{s/p}, b_{s/p} \in [0,1] \\ m_{s/p}(\Theta) = 1 - b_{s/p} \\ m_{s/p}(\emptyset) = 0 \end{array} \quad (11)$$

Relatively to a space point p, a sensor s provides $m_{s/p}$ as a belief function. To decide whether p is covered by s, the pignistic transformation of $m_{s/p}$ (denoted by $BetP_{s/p}$)is constructed. The decision is based on selecting the hypothesis $\hat{\theta}$ with the largest pignistic probability $\hat{\theta} = \underset{i=0,1}{\operatorname{argmax}} BetP_{s/p}(\{\theta_i\})$.

A space point p is covered by a sensor s if:

$$\begin{array}{c} \hat{\theta} = \theta_1 \\ BetP_{s/p}(\{\theta_i\}) = Th_p \end{array} \quad (12)$$

The threshold (Th_p) value is an application-specific user-specified parameter.

One current application of WSNs is target/event detection; the sensors collaborate to arrive at a consensus decision as to whether a target is present in the RoI. A TBM-based approach is considered for reaching this consensus: one of the sensors (called a fusion center: it can be a sink, a cluster-head or any sensor), gathers the evidence from the other sensors, combines the evidence and decides whether an event is present or not.

IV. EVIDENTIAL NETWORKS

In order to take advantage of the two approaches mentioned so far, it is possible to combine TBM and Bayesian Networks.

A. Principles

Basic approaches enable this integration but are limited to binary variables [13]. Evidential networks, introduced in [14] and developed in [15], use conditional belief functions for belief propagation in acyclic oriented graphs. Each node of the evidential network represents a random variable that is associated with a finite number of values. Directed evidentials networks were introduced in [16].

In the same way as evidential networks, they use conditional belief functions to propagate the belief in graphs without circuit. This formalism is very close to Bayesian networks but uses conditional beliefs instead of conditional probability functions [17]. Each arc of the graph represents a conditional relationship between two variables, represented by nodes. Each variable is set to a FoD representing the set of values it can take. Parent nodes are characterized by a priori belief functions whereas child nodes are represented by belief functions conditioned by their parent values.

The Generalized Bayes Theorem (GBT) and the Disjunctive Combination Rule (DCR) are used to infer and propagate the knowledge in the network. Figure 4 represents a very simple directed evidential network with only two nodes, Θ and Ω and one arc representing the causal relationship between the nodes. From the perspective of the variables, which are represented by nodes, the edge indicates that node Ω, which represents the observation space characterized by a priori belief mass distribution, noted m_0^{Ω}, is conditioned by node Θ, standing for the hypothesis space characterized by a conditional belief mass distribution $m^{\Omega}[\theta]$.

There are several ways to propagate knowledge in a directed evidential network depending on the node receiving the current knowledge expressed in the form of a new belief mass distribution [14].

$$\Theta \longrightarrow \Omega$$

Figure 4: Basic directed evidential network

The knowledge is spread in the direction of the arc if the Θ node receives a new distribution of masses m^{Θ}, the Ω node is then updated taking into account this new information. This type of spread, called forward propagation enables the calculation of the distribution of plausibility Pl^{Ω} using the equation of the GBT based on an a priori knowledge. This equation uses the DCR rule to determine the plausibility $Pl^{\Omega}[\theta_i]$] for each subset $\theta_i \in \Theta$ and evaluate Pl^{Ω} by combining the conditional plausibilities $Pl^{\Omega}[\theta_i]$ using the Conjunctive Combination Rule (CCR).

The knowledge can also be propagated in the opposite direction of the arc if the Ω node receives a new distribution of masses m^{Ω}. The information contained in the Θ node is therefore updated to take account of this new information. This type of spread, called backward propagation enables the calculation of the plausibility distribution Pl^{Θ} by using the following equation:

$$Pl^{\Theta}(\theta) = \sum_{\omega \subseteq \Omega} m^{\Omega}(\omega) \times \left(1 - \prod_{\omega_i \subseteq \omega}\left(1 - Pl^{\Theta}[\omega_i](\theta)\right)\right), \forall \theta \subseteq \Theta \quad (13)$$

B. Case Study

A case study using evidential network applied to sensor networks is being processed (Figure 5). It is related to Advanced Sensor Technologies for Nondestructive Testing (NDT) in the field of aeronautics Structural Health Monitoring (SHM). Sensors based on ultrasonic or Eddy Current techniques are arranged on an aircraft structure to measure the level of damage. Functional recycling of products or just testing the integrity of an aeronautical structure (fuselage or wing of an airplane for example) requires a diagnosis of their current state.

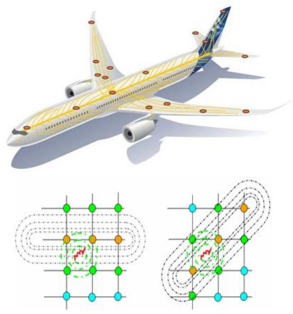

Figure 5: Instrumented aircraft monitored by sensor networks

The main goal is to detect, locate and identify defects, and, subsequently, follow their evolution. The use of NDT techniques allows the decision-maker to call on the compliance of the parts analyzed by quantification of the level of damage. The discussed example aims to develop an informational interface based on an evidential networks superimposed on the NDT sensor network for the interpretation of the signals received and the decision support. The position and the number of sensors lead to a level of uncertainty characterized by belief functions introduced and propagated in the evidential network.

As a possible illustration of the interest of using evidential networks and with respect to the sensor architecture, as well as the emitted and received signals, one can use here this technique both to:

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TABLE I. COMPARISON OF FORMALISMS

	Uncertainty kind	Amount of data	Causality modeling	Computational complexity
Bayesian networks	Random uncertainty	High (frequentist approach) Low (Subjectivist approach)	Yes	Low to Mean (depending on the complexity of the network)
Belief functions	Random and epistemic uncertainties	Low	No	Low to mean (depending on the number of singletons of the variables)
Directed evidential networks	Random and epistemic uncertainties	Low	Yes	Very High

- predict the presence of a defect in a forward propagation of the marginal belief functions knowing the signal values
- predict the detection of a defect in a backward propagation of the conditional belief function knowing the existence of a proven deterioration or failure.

We may observe also that upon receiving the information where a particular defect has been detected by any one of several distinct sensors, one can identify the source as belonging to this set. Therefore, one can assign the belief that the signal is present to the set of possibilities. The use of a Bayesian network would have forced to distribute this belief over all the individual nodes (sensors). Evidential reasoning avoids so the need for assumptions on missing data. When beliefs on a sensor is later required they are under constrained resulting from the disjunction and an interval representation is needed to capture the real constraint which enable the explicit representation of uncertain and certain knowledge.

V. COMPARISON OF FORMALISMS

As we mentioned above, each presented formalism aims at modeling and reasoning under uncertainty. However, their conditions of application are different and some are better than others in given circumstances. Table 1 positions the three formalisms (Bayesian Networks, belief functions, evidential Networks) according to four criteria: the kind of uncertainty addressed, the minimum amount of data required, the capacity to model causality and the computational complexity (in relation with the computation time).

VI. CONCLUSION

The purpose of this paper was to present several techniques to introduce the notion of uncertainty in the use of sensor networks. The underlying idea is to be able to assess the measurement error and the corresponding risk to reduce the oversizing of the monitoring architectures and better define the level of confidence placed in the information received from the network. After presenting approaches respectively based on Bayesian Networks and Belief Functions, Evidential Networks have been introduced. The interest of their use lies in their ability to spread non-probabilistic knowledge according to forward or backward modes of propagation to facilitate dynamic decision making.

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