Modelling a large scale system for risk assessment

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***Abstract*—The aim of this communication is to present an earlier study of how to structure modelling process of complex and large scale systems for risk assessment and management purpose. The approach, in a first stage, uses ontology paradigm to determine variables (or concepts) characterizing system locally and the nature of relationships relating them and, in a second stage, object oriented Bayesian network (OOBN) to characterize the strength of these relationships in terms of conditional probabilities tables given that one of main feature of complex systems is the uncertainty that affect the relationships between different variables. A case study in the domain of risk assessment of flash floods effect on the infrastructures inoperability is considered to show potential applicability of the developed approach.**

Keywords*—complex systems; interdependency; modelling; ontology; OOBN

I. Introduction

Capabilities of many systems (transportation infrastructures, energy and water supply infrastructures, communication infrastructures, production infrastructures, financial infrastructures, etc.) that facilitate modern life in many ways are highly interdependent, complex and evolve on a large scale. Within this context, disturbances of any entity in such formed network is likely to affect other entities by risk propagation mechanism. Integration of risk factors in decision making or risk informed decision making is receiving a great attention by researchers and decision makers in many domains such as engineering (designing technical systems that mitt some requirements in terms of safety), finance (setting up norms to monitor finance activities in order to avoid companies collapse), environment (developing sustainable agriculture and natural resources extraction actions), science and medical research (monitoring scientists activity by the society to avoid creating new threats); because national and international opinions are being more and more concerned by risk issues from all human activities as well as natural phenomena (earthquake, hurricane, tsunami, floods, etc.). Risk comes from the incapacity of human beings to correctly predict the outcomes of some events from the environment of the system under consideration or their actions on this system. Indeed, risk and uncertainty are fundamental elements of modern life so they must be addressed properly to protect people from injury. Today an ever-increasing number of professionals and managers in industry, government, and academia are devoting a larger portion of their time and resources to the task of improving their approach and understanding of, risk-based decision making. Indeed, decision making under uncertainty (risk) literally encompasses every facet, dimension, and aspect of our lives. Any decision maker needs to cope with uncertainty in order to rationally act in the sense of risks reduction. To correctly and scientifically address risk management process that is assessing, filtering risk factors, selecting and prioritizing appropriate actions, one needs to dispose of sound models able to reproduce the functional and dysfunctional aspects associated with an anthropic or natural system. These models should permit manager to take decisions of three types: pre-active decisions, these decisions consist in doing things to prepare the system under consideration to face potential adverse events (one knows that such events will occur soon or later). Actions such as transferring risk by contracting insurances, editing anti-seismic construction norms in the case of natural disasters, preparing population on how to behave in the case of an earthquake, constructing and organizing emergency facilities, etc. are proactive decisions. One may need also need reactive decisions that are real time decisions to be made when the undesirable event does really occurs and pro-active decisions that consists in doing things to avoid the occurrence of catastrophe when possible for instance [1]. This necessity of disposing of sound models is of great importance in the case of complex interdependent systems evolving on a large scale. The remainder of this communication is organized as follows: in the second section, main features of complex interdependent systems are briefly presented together with the necessity of disposing of a structured tool for the modelling process; section three presents a state of the art on ontology and object oriented Bayesian network (OOBN) approaches as structuring tools that can potentially respond to our needs; and finally section four considers applying these approaches for modelling flash floods phenomena in order to assess risk faced by infrastructures in zone where these phenomena take place.

II. Complex system

A. Main features of a complex system

A complex system is constituted by many entities, components or variables with mutual relationships. The complexity is exacerbated by the uncertainty that may affect these relationships. The behavior of the system is highly unpredictable without a sound model. The purpose of this communication is therefore to develop an approach that can be used for the modelling of complex systems with the ultimate purpose to assess the risk facing some components of the systems when one of the components is destabilized by an external event for instance. Such a generic model can be used in many socio-economic domains to assist the assessment of indicators or the decision making. The modelling process must rely on logical and structuring tools in order to avoid incomplete, imperfect or faulty models; next paragraph reviews existing approaches and proposes those that can be used or adapted to fulfill our needs.

B. Structured modelling necessity

Classical analytic approaches that suppose many simplifying hypothesis are not suited to deal with all aspects of complex large scale interdependent systems. When it is possible to collect data driving the behavior of a complex system, learning approach offers the possibility to build a model that will be able to reproduce, by feedback mechanism, the behavior of the system as accurate as possible. Learning is an artificial intelligence approach that permits to relate input data (causes) of a system to the observations (consequences or output). The learning process may consist in determining the internal structure of the system that is identifying relationships (or interactions) between its different components referred to as structure learning; or in determining the strength of interactions between components of a system with known structure known in the literature as parameter learning. Within this framework, Bayesian Networks (BN) are very efficient for modelling uncertainties. Dynamic Bayesian Network (DBN) may be used when temporal dimension in the behavior of the system is to be taken into [2]. In DBN, each sample instant t of time horizon is constituted by a BN. For BN, there exist many learning (mainly in what concern parameters learning) sound and powerful algorithms in the literature ; this is not the case for DBN for which existing learning algorithms are so complicated that their deployment in real world applications is not easy mainly in the case of systems with a huge number of components. A possibility to reduce this complexity is to use the so called Object Oriented BN (OOBN) in order to exploit possibilities offered by this modelling technique. The idea of modelling repeatable systems by object oriented techniques has been already considered in a certain number of studies such as works undertaken in references [3], [4], [5] to mention just a few.

III. State of the art

Existing approaches

Object Oriented Bayesian Network (OOBN) standpoint

Bayesian Networks are used to formalize knowledge in the form of a causal graph associated with a probability space [6], [7]. They are directed acyclic graphs (DAGs) 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:

- a graph-oriented without circuit, noted $\mathcal{G} = (\mathcal{V}, \varepsilon)$, with $\mathcal{V}$, the set of nodes of $\mathcal{G}$, and ε, 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 $\sigma - algebra$ on Ω and $\mathcal{P}$ is a measure on Ω such that $\mathcal{P}(\Omega) = 1$; $\mathcal{P}(\textit{empty set}) = 0$; $\mathcal{P}(A) <= \mathcal{P}(B)$ if A included in B,
- 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: $\mathcal{P}(\mathcal{V}_1, \mathcal{V}_2, ..., \mathcal{V}_n) = \Pi_{i=1}^{n} \mathcal{P}(\mathcal{V}_i | pa(\mathcal{V}_i))$

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 [8]. Tables of prior probabilities characterizes the chances that the variable $\mathcal{V}_a$ without any parent is in state a_i. Tables of conditional probabilities establish the chances that a variable $\mathcal{V}_b$ is in state b_j based on the state of its parents [9], [8]. Inference in a Bayesian network consists in propagating information in the network [10], [11]. 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 [12]. This new knowledge, takes the form of a so-called elementary information, denoted $\mathcal{J}$, relative to a particular node. There are two types of basic information. The deterministic information allows instantiating a variable, that is affecting it a precise value, (eg $\mathcal{P}(\mathcal{V}_a = a_1 | \mathcal{J}) = 1$). The imprecise information modifies the distribution of probability of the variable, either by excluding a value of the universe of the variable ($\mathcal{P}(\mathcal{V}_a = a_1 | \mathcal{J}) = 0$) or, more usually, by changing the law ($\mathcal{P}(\mathcal{V}_a = a_1 | \mathcal{J}) \neq \mathcal{P}(\mathcal{V}_a = a_1)$).

The structured representation offered by the object oriented techniques enables to improve the performance of the Bayesian Networks in terms of complexity of specification and inference of large systems. An object-oriented Bayesian network, is a direct application of the object paradigm. The basic element is the class, fragment of a Bayesian network whose nodes are broken down into three sets: input and output interfaces together with internal nodes. The object oriented Bayesian network takes advantage of classic Bayesian networks but introduce the concept of instance nodes. An instance node is an abstraction of a part of a network into a single unit. Consequently, instance nodes can be used to represent different network classes within other networks. The notion of encapsulation allows the transmission of all properties of the net fragment. An object-oriented network can be viewed as a hierarchical description/model of a problem domain. This makes the modelling easier since the OOBN-fragments at different levels of abstraction are more readable.

An example of an OOBN is presented in figure 1. Based on [13] the model introduces four classes, namely: rain, melting water, irrigation water and occult water. Inputs are represented by dotted line such as energy or thickness, outputs are characterized by solid lines like for instance water state and water volume. Interstructure associated with internal nodes is encapsulated in each class.

Once the structure and relationships between the nodes has been established, the main work consists in characterizing the Conditional Probability Tables (CPT). Building OOBN model may be somehow difficult when it concerns a complex system with many variables, states or relationships. The use of learning techniques might bring some help for the identification of

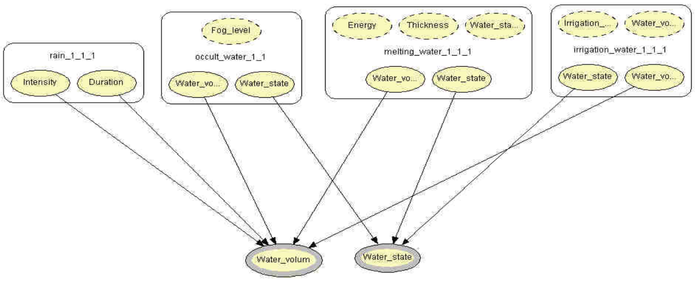

Fig. 1. OOBN model of water supply

the relationship between nodes as well as the CPTs values. In[14], [15] the authors give some insight over OOBN structure learning. In [16] the author extends the parameter learning based on OO assumption and propose a parameter learning method based on the reducing of the parameter number during the learning phase.

Ontology standpoint

Historically, ontologies has a metaphysical origin by a philosophical perception, arriving in computer science with a more technical view.

On a computer view, an ontology is an explicit specification of a conceptualization [17]. Currently, principles for the design of ontologies are means of providing a structured representation of knowledge from real world at different levels of abstraction and modelling (e.g. domain ontology or upper ontology). The purpose of employing an ontological representation is to build a common understandable model for collaborative practices and knowledge sharing to apply reusable problem-solving techniques ([18], [19], [20]). Here we will use the example in Figure 1.

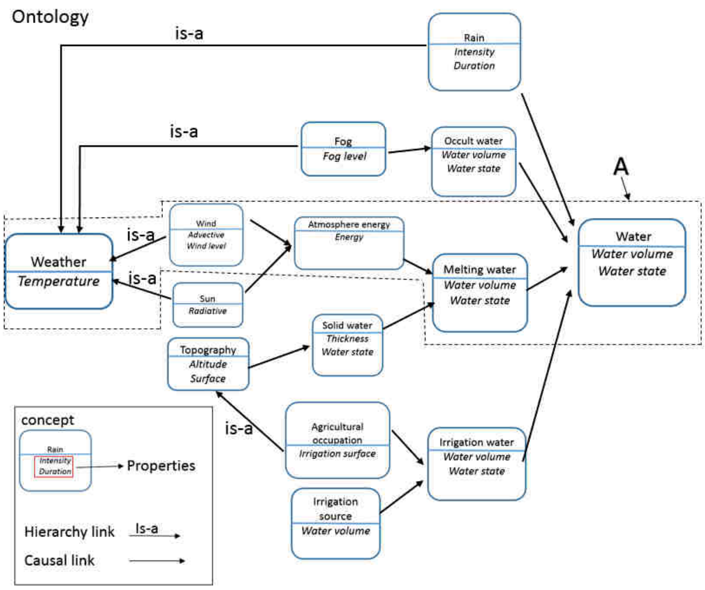

Fig. 2. Ontology model of water supply

The concepts have their own properties, shown in the table below:

Concept	Property
Water	Water volume, water state
Topography	Altitude, surface
Atmosphere energy	Energy

Nowadays, the fundamental meaning within artificial intelligence is a semantic model for specifying the used vocabulary that consists of a set of types of concepts, relations and their associated properties. This formal vocabulary is essential to capture and formalize the structured information needed for knowledge representation and reasoning [20]. Hence a key benefit of using ontology is the opportunity to improve mechanisms of reasoning in the target models. So, for a special complex large real system, the generated models are semantically more informative than statistical models like Bayesian Network, since it provides a formal semantics that is a sound basis for the computerized reasoning and knowledge exploitation. In light of these characteristics, ontological models are complementary to numerical models in modelling the complex systems for risk assessment. For instance, as part of a flood forecasting system, procedural knowledge encoded in the domain-specific ontology can be triggered to monitor and display water conditions in the modelling of risk (Figure 2).

Ontology and OOBN

Ontology lacks the quantification part. That is the reason why some researchers work to combine the probabilistic and ontology language ([18], [21]) so that they can enrich each other. There are two main directions, one is to enhance ontology capabilities to support probabilistic inference, the other one is to enhance the probabilistic graphical models construction by integrating ontologies [22].

Bayesian Network as a knowledge-based network presents quantitative as well as qualitative information. The qualitative part presents the system by a graph, and the quantitative part defines the conditional probability for each node in the graph.

As we mentioned it previously, although there exist some learning methods in the literature to building the structure of BN, the construction of the model is still a big issue for BN design and development. Ontology model can qualify the knowledge clearly and simply through modern languages like OWL (Web Ontology Language), DALM+OIL for instance. Let us note that some work has already been undertaken on how inserting probabilistic reasoning in the ontology language, and most of them have concluded that BN was the appropriate tool for that [18], [19], [20]. An approach of combining ontology and BN is presented in [20].

Others researches like [18], [19], [21], [23], [24] give some ways for extending an ontology to BN. Indeed, there are already some means to proceed to the transformation, but the quantitative part remains difficult.

Based on [22], equivalence between ontologies and object oriented bayesian network has been identified.

OOBN	Ontology
Class-Instance	Concept
Input reference nodes	Properties
Internal nodes	Properties
Output nodes	Properties
Class hierarchy	Is-a

In this research the author treats the concept as an instantiation of class, but not all the concepts in an ontology can be represented by a class level.

IV. Proposed approach

Introduction

In this part, we propose to use the ontology model to help building the BNs. As mentioned earlier, due do some limitation of the BNs for the complex system representation we will use OOBNs which are more expressive than the standard BN in order to address an extended range of ontology [22]. Research carried out in [22] deals with an approach for translating an ontology model to OOBN, including a set of mapping rules allowing to generate a prior OOBN structure by morphing an ontology related to the problem under study to be used as a starting point to the global OOBN building algorithm. Research done in [24] is interesting because it shows how translating an ontology model into a two level Bayesian networks.

From Ontology to OOBN

In the following this paper assumes that all semantic relations present in the ontology are of a causal orientation. We first defines a simple concept and a normal concept in ontology. The simple concept has no property and influence other concept only by itself. The normal concept has one or more properties.

The reason of distinguishing simple concept and normal concept is mainly due to the possibility of associating directly a node to the simple concept in the future Bayesian network. It makes thus easier the modelling process.

Proposition: A simple concept correspond to a node in OOBN (see [19]).

We use the generic Depth-First Search (DFS) algorithm from [25] for graph building. We give below a stepwise approach on how converting an ontology representation into an OOBN.

1) Distinguish each concept CP_i by separating simple concept and normal concept;
2) Use Depth-First Search in ontology model for finding every branch $b_1, b_2, ..., b_n$;
3) Build a directed acyclic graph (DAG) in class level;
4) Transfer the class level DAG to a OOBN.

We present now a brief description of each step of the approach.

Step 1: ***Identification of simple or normal concepts***

- Check the property of each concept;
- Put the no property-concept in a 'concept-node'box;
- Put the property-concept in a 'concept-class'box.

The concept in concept-node box corresponds to a simple node in OOBN [19]. Without any precision, the concept is considered to be a normal concept.

Step 2: ***Depth-First-Search algorithm(see [25]).*** We will illustrate this step by its application on the example provided in Figure 2. On branch A appear causal links and hierarchy links. When there is a hierarchy link "is-a", the **upperconcept** will appear in the **subconcept** placed in parentheses for underlying the difference. Applying the DFS algorithm allows the identification of the order of the concepts to be encapsulated. In this example the DFS algorithm leads to the following order: **Wind(Weather)**, **Atmosphere energy**, **Melting water** and **Net water**.

Step 3: ***Building a Directed Acyclic Graph (DAG)***

- Associate each concept CP_i to a node C_i in the DAG G;
- Add the link in DAG by keeping the direction of the correspond link in ontology model;
- If the link in ontology belongs to a "is-a" type, use a hierarchy link in DAG with the direction from class to subclass; for example, if CP_{ia} "is-a" CP_i, we have $CP_i \Longrightarrow CP_{ia}$, where CP_{ia} is called a *subclass node of* CP_i;
- Add a "cause-effect" linkage for each hierarchy link with the descendant of its subclass node in DAG.

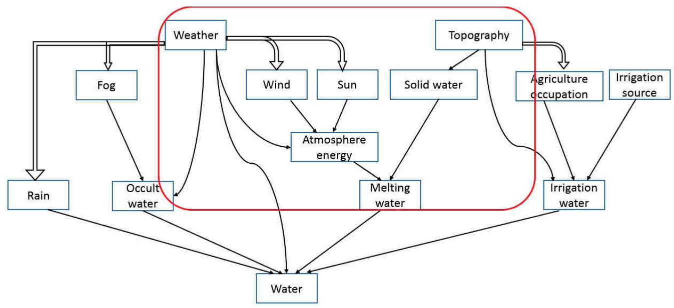

Fig. 3. Ontology model of water supply to a DAG in class level

Using the example from Figure 2 and Algorithm, CP_i to a DAG in class level we obtain the model in Figure 3.

Step 4: ***Translating a DAG into an OOBN***

- Find the root cause of each branch (using DFS) which is the deepest instantiation;
- Each property p_{ki} in a concept is its own output node of class-instantiation $I_i : C_i$ correspond in OOBN, add the output nodes at this class;
- The cause class-instantiation gives the input informations/nodes of the effect class, add the input node at the effect class-instantiation;
- Repeat the same processes below until meeting a hierarchy link $\Longrightarrow$;
- Hierarchy link $\Longrightarrow$ means the output nodes in cause class are the input nodes at the effect class, and the

class node does not provide the information for its subclass node;

- Add a construction link “- -” between the class node and its subclass node.

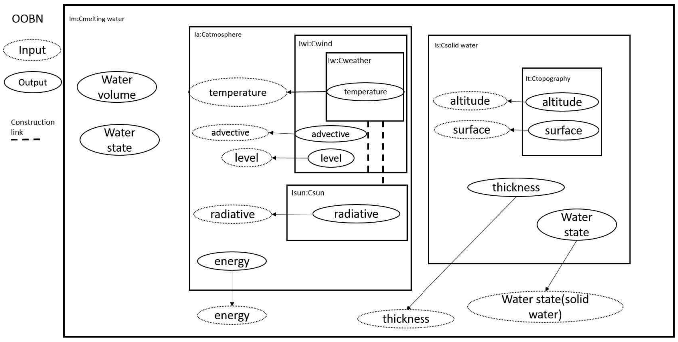

Fig. 4. OOBN at instatiation level

Using this algorithm on the square part of Figure 3, we obtain results in the OOBN of Figure 4.

Ontology represents the relationships between concepts. The corresponding algorithms [22] will have to be improved in a near future to take into account into the OOBN of the internal nodes and links.

V. Case study: modelling flash flood effect

Climate change has contributed to an increase in extreme weather events. Scientists predict that climate changes will increase the frequency of heavy rains, putting many communities at risk of flooding. In mountainous areas, this risk is increased by the relief and its consequences in terms of water flow kinematics.Flood torrents directly threaten human and material issues due to the intensity and suddenness of the events. The implementation of methods of protection, prevention, security and control of the risk of flooding in general requires a better knowledge of the phenomena of floods and, thus, a better ability to model these phenomena.Flood risk analyses are important insofar as they allow the assessment of the economic efficiency of the mitigation measures and optimize investments envisaged for the protection of population and infrastructure. Facing a potential, announced or proven crisis, they lead to a better design of insurance policies and actions of anticipation or remediation implemented by companies, municipalities or even citizens.

The most common approach to define flood risk requires to combine a hazard characterized by statistical aspects (frequency of occurrence) and physical aspects (flow intensity) and an impact expressed in terms of vulnerability; i.e. exposure and sensitivity of persons and goods to potential damages.

Torrential floods are rapid gravity phenomena which include a share of irreducible uncertainty related to randomness events (rain, snow...) and to the knowledge of the involved processes. Risk management decisions must compose and integrate this stochastic dimension.

Bayesian networks seem a suitable tool for the implantation of such a model see [26]. The modelling work which is in progress has been divided into 2 parts. It consists first in identifying the influential parameters in the generation of the flood phenomenon. It endeavours to determine the cognitive structure to retrieve the corresponding information from networks of sensors, databases, expertise... Within this framework, the passage through an ontological approach is crucial and represents a natural framework to structure the problem. The second part aims to create a spatio-temporal causal model for the explanation and the probabilization of the feared events for diagnostic and prognostic purposes.

As a first step, an elementary time-independent Bayesian network will be established to characterize the influence of variables on a small geographical area homogeneous in terms of topology.

In order to characterize the spatiality of the phenomenon, the idea is then to exploit this basic model as a generic block of modelling, characteristic of the evolution of all of the variables that may be brought into play, and then to associate the different bricks instantiated with respect to the considered area and sequenced temporally according to the phenomenon timeline.

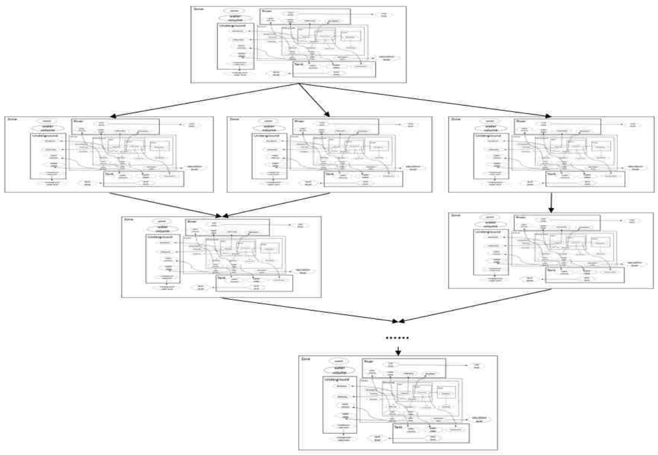

Fig. 6. OOBN of an extended geographical zone

Objects Oriented Bayesian Networks appear to be appropriate to characterize this chronology characterized by similar variables instantiated according to the corresponding spot. Figure 5 gives a simplified view of the modelling elementary block whilst Figure 6 represents the model of an extended geographical zone.

VI. Conclusion

The present work deals with the modelling and analysis of complex systems characterized, in an uncertain and evolving framework by many interactions between components. With the objective of representing large and repetitive structure in such a context , oriented object probabilistic models seem an appropriate solution. Within this framework object oriented Bayesian Networks (OOBN) appear as powerful and well suited to the representation of complex models submitted in part to random events. To facilitate the characterization of this type of model, an ontology-based approach is presented. An algorithm is then used to translate the ontological model into an object oriented Bayesian network. An illustration of the

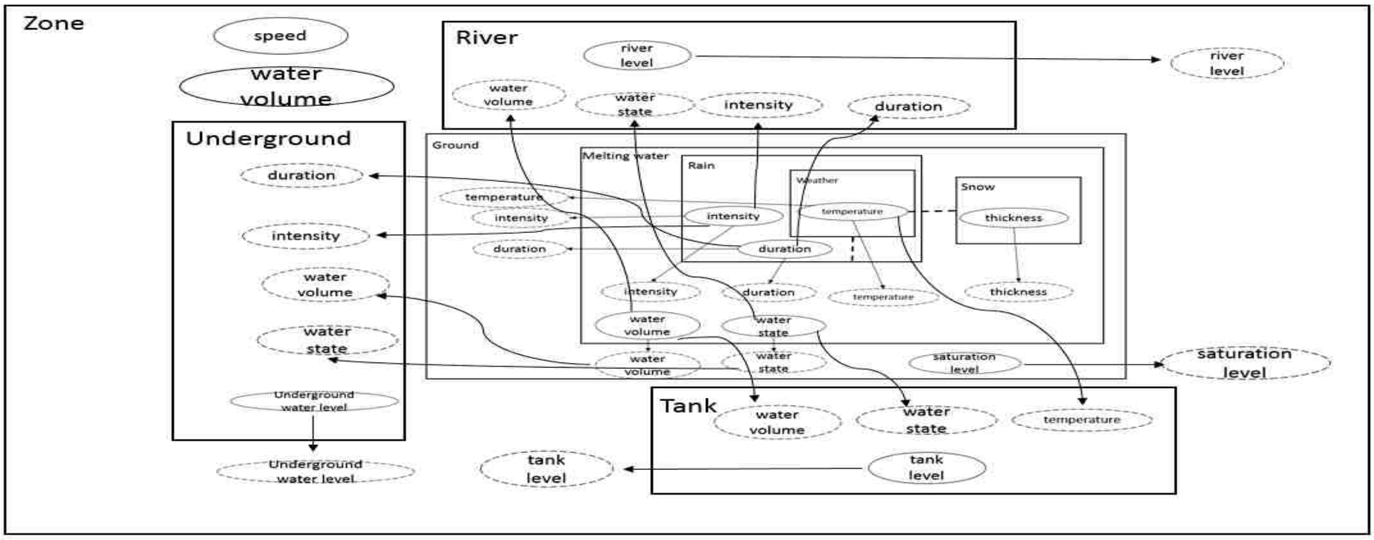

Fig. 5. OOBN of modelling elementary block

principles introduced in the article concerns the modelling of the risk of flash flooding related to a specific geographic area. After showing the construction of the object oriented Bayesian network on a small and homogeneous geographical area with respect to topology characteristics, the extension of this basic model is proposed for the representation of a wider territory.

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