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# 1 Graph based knowledge models for capitalizing, predicting and 2 learning: a proof of concept applied to the dam systems

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7

8 **Abstract:** The capitalization and the analysis of historical information is nowadays a prerequisite for any  
9 effective risk management and assessment in a wide range of domains. Despite the development of mathematical  
10 models, procedures, support decision systems and databases, some engineering disciplines, such as civil  
11 engineering, remain resistant to the use of new digital technology due to the gap between the expectations of the  
12 engineers and the support that the tools may really provide. It is essential to propose a tool able to process both  
13 cross disciplinary and interdisciplinary knowledge flux and feedback from experience in a common and  
14 convenient unifying framework. The aim is to assist and to support engineering work and to make the task of  
15 knowledge modelling easier. The domain of dam systems is no exception to the rule. Dam failures are still  
16 commonplace. These failures stem from a lack of understanding about the complex relationships between three  
17 different factors: random hazards, the limit states of dam structures along with human activities and decisions.  
18 No generic and holistic approach is currently available that permits the processing of both knowledge and data,  
19 performs inferences and is easily usable for all types of users. This paper proposes the basic principles of a  
20 convenient design methodology for capitalizing, learning and predicting based on the formalism of conceptual  
21 graphs. The aim is to provide an easily usable tool able to (1) capitalise heterogeneous knowledge and store a  
22 database about dams, (2) issue alerts on current projects, (3) draw lessons from past dam failures and (4) tackle  
23 key issues in forensic civil engineering.

24 **Keywords:** Knowledge representation, conceptual graph, dam failure, forensic engineering

## 25 1. Introduction

26 In this paper, knowledge corresponds to general concepts representing a set of things with a common meaning in  
27 a domain and data correspond to specific instances (Wiederhold, 1986). With the explosion of data availability,  
28 digitized engineering works and knowledge due to technological advances, capitalization and analysis of  
29 historical information is nowadays a prerequisite for any effective risk management and assessment in a wide  
30 range of domains (agri-food, biomedicine, petrophysics, etc). It is a priority among researchers and industrials  
31 from diverse backgrounds (Buche et al., 2019; Cárdenas et al., 2013; Giacona et al., 2019). To better understand  
32 failure and damages to systems caused by natural phenomena over time or human intervention, it is necessary to  
33 acquire, structure, model, and share cross disciplinary and interdisciplinary knowledge flows in a common and

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34 unifying framework (Bokade et al., 2021 ; Kamsu-Foguem and Noyes, 2013). Nevertheless, this is not an easy  
35 task given the heterogeneous character of the sources of knowledge and manipulated scales.

36

37 The domain of dam systems is no exception to the rule. Dam systems are an important part of the infrastructure  
38 systems of many countries. They meet demands for irrigation and agriculture, energy generation, flood control,  
39 domestic use, storage of mining by-products, etc. The Association of State Dam Safety Officials (“Dam Failures  
40 and Incidents | Association of State Dam Safety,” n.d.) reported in the U.S 251 dam failures and 547 "incidents"  
41 from 2010 through 2020 where 64 (*resp.* 38) of them have the incident mechanism (*resp.* incident driver)  
42 unknown. The unknown character of the incident driver supposes human failings, human errors due to the non-  
43 compliance of rules regarding the design, the construction and the operations of dams (Adamo et al., 2020).  
44 Despite (1) the development of decision support systems to better understand and to manage the complexity of  
45 dam systems and (2) the new building standards imposed by the public authorities after each dam failure; dams  
46 are still today confronted with failures that can lead to dramatic situations (Silva Rotta et al., 2020; Latrubesse et  
47 al., 2020). Blockley (1980) identified 3 main types of structural failure causes: limit states (overload, corrosion,  
48 erosion ...), random hazards (floods, earthquake ...) and human based errors (design error, poor communication,  
49 mistakes...). Dam systems are complex systems (Northrop, 2014) in that the interactions of the individual  
50 components at different levels, in uncertain environments (natural hazards, stakeholder behaviours, construction  
51 activities, *etc*) determine the emergent functionalities and properties, which individually do not exist. It would  
52 not be consistent and sufficient to individually analyse each component against a prescribed standard to assure  
53 the safety of dams (Regan, 2010). Tackling this complexity through interdisciplinary fields (artificial  
54 intelligence, civil engineering, forensic engineering) could improve our grasp of the system in a holistic way, and  
55 provide more robust and efficient decision making alternatives in risk management (Choi and Pak, 2006). It is  
56 then essential to propose conceptual approaches able to assemble the puzzle of knowledge regarding the studied  
57 system in order to assist and to support engineering work and hopefully to make the task of knowledge  
58 modelling easier.

59

60 Current research, to represent complex systems, relies on the development of networks in which nodes represent  
61 entities and the links represent their relationships (Boccaletti et al., 2006). The framework of conceptual graphs  
62 (CGs) provides a practical and attractive mathematical formalism that permits the management of terminology,  
63 the facts, the rules and the complex computations of an application domain (Jr, 1983, Chein and Mugnier, 2009).  
64 The expressive power of CGs and their capacity to formalize procedural and declarative knowledge have been  
65 widely proven in the domain of agri-food and successfully used to implement decision support systems (DSSs)  
66 (Thomopoulos et al., 2009; Martin et al., 2020; Buche et al., 2019). The resulting DSS allows users (1) to control  
67 quality and defects of food manufacturing by recommending relevant actions and (2) determine the  
68 consequences on food product quality given the supported actions. This formalism has been investigated in  
69 medical domains (Doubouya et al., 2015) as well as others, from industry (Kamsu-Foguem et al., 2019) to  
70 natural language processing (Boonpa et al., 2017). Reasoning in these DSSs mainly consists in applying  
71 iteratively a set of rules based on the first order logic. By associating a scripting language with the formalism of  
72 CGs, it will then be possible to take complex physical, mechanical, *etc* behaviours into account.

73

74 Within an approach of engineering informatics, the aim of this paper is to propose a flexible and usable tool  
75 capable of integrating the interconnected information flow between computing, computational method and  
76 engineering related to civil engineering infrastructures. The development of the tool is based on an innovative  
77 graph-based knowledge model of Dam systems relying on conceptual graphs (CGs) and must be able to

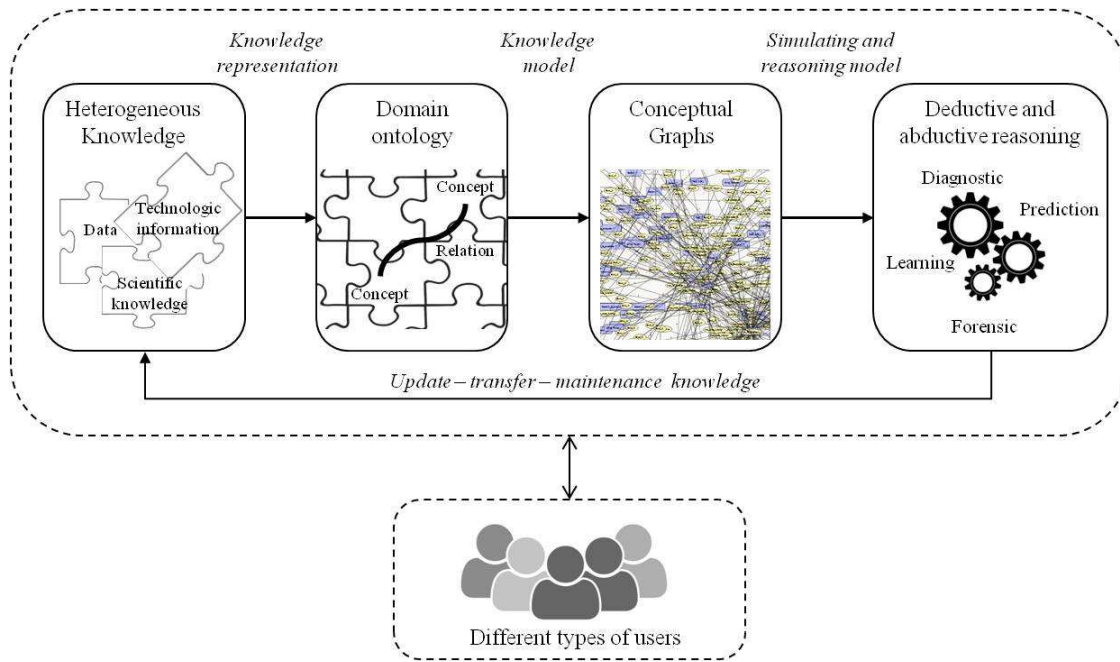
- 78 • assist in practice experts and engineer users not only to structure and enter the pieces of knowledge to  
79 build the model but also to understand and to control the results of the model and how the model  
80 computed these results.
- 81 • provide a generic skeleton to represent any kind of dam system in its environment using a common and  
82 controlled vocabulary
- 83 • instantiate, implement and store a database containing factual knowledge relative to any kind of dam  
84 system in its environment, and dam failures
- 85 • estimate the current and the future states of dam systems regarding uncertainty by integrating  
86 simulating models,
- 87 • identify possible mechanisms, phenomena, human behaviours, etc which can lead to a dam failure  
88 known as forensic engineering (Noon, n.d.)
- 89 • be enriched and updated each time new information is available without damage to the whole structure  
90 of the model and the graph-database

91

92 Figure 1 summarizes the workflow process for building the tool that facilitates knowledge integration and  
93 utilization for improving the operations of dam systems throughout their lifecycle. All kinds of knowledge are  
94 represented by means of graphs and thus may be visualized, managed and updated in a natural way by a range of  
95 users including engineering experts, designers, etc. It is important to realize that the presented paper is a proof of  
96 concept applied to dams while it also provides an overview of the potential of the graph formalism. Theoretical  
97 simplified models are used for demonstration purposes.

98

99 The article is organized as follows: Section 2 reviews related works; Section 3 details the material regarding the  
100 conceptual graph models; Section 4 proposes the graph-based knowledge model for representing any kind of  
101 dam system and Section 5 illustrates the use of the developed graph-based knowledge model in the framework of  
102 diagnostic, prediction and forensic engineering.



103  
104 **Figure 1 :** The iterative design process of the graph based knowledge model

105 **2. Related works**

106 There have been many different approaches and tools devised to support engineers in their work. These tools  
107 focus on providing support in several areas: the formalization and representation of knowledge, data analysis and  
108 process modelling and simulation. In civil engineering, the aim of these tools is (i) to design and evaluate safe  
109 infrastructure, (ii) to predict the future state and function of civil engineering systems in operation and when  
110 failures occur, (iii) to explain the likely causes.

111  
112 Knowledge-Based Engineering (KBE) and Knowledge-Based System (KBS) are examples of such tools. These  
113 digital tools have been developed by integrating knowledge in the form of rules and constraints. They are  
114 capable of integrating different sources of knowledge for the capture, storage and reuse of engineering  
115 knowledge. They are composed of two distinguishing features: a knowledge base (representing facts about the  
116 studied domain) and an inference engine (rule systems capable of deducing new information). Although KBE  
117 and KBS have been successfully developed and used in various domains (Häußler and Borrmann, 2021) their  
118 implementation still requires significant effort and remains case dependent. They tend to be ‘black box’ type  
119 applications, lacking explanations and thus complicating the reuse of the knowledge found within the KBE  
120 system (Verhagen et al., 2012).

121  
122 Failure mode and effects analysis (FMEA, (Fonseca and Ávila, 2016)), fault tree analysis or simple failure  
123 analysis (FTA, (Ren et al., 2012)) are popular methods used in civil engineering to collect and analyze  
124 knowledge used to determine the causes and effects of dam failures and set up actions to prevent failures (Amin  
125 et al., 2019). As with KBE and KBS, the construction of these methods requires a large amount of effort, and  
126 they remain dependent on the system studied. Furthermore, fault tree analysis and its extensions (fuzzy,  
127 probabilistic FTA) are limited by the use of Boolean algebra which assumes **all failures are binary meaning that**  
128 **components are** either failed or working (Baig et al., 2013).

129 Other Expert Systems have been developed using rule bases, fuzzy rule bases and logic to evaluate the safety of  
130 dams (Ribas and Pérez-Díaz, 2019, Supakchukul et al., 2019 ; Curt et al., 2011 ; Curt et al., 2010). No matter  
131 which approach is used, it still requires a case-by-case description of the dam specifics and the developed models  
132 are dependent on dam type. Numerical models have been developed to simulate the physical and mechanical  
133 behaviour of dams, these are usually based on finite element methods (Haiqing et al., 2004; Chen et al., 2019;  
134 Kojima et al., 2020; Hariri-Ardebili, 2020). Unfortunately, numerical approaches imply large degrees of freedom  
135 in the finite element models and mainly consider the technical aspects of failures.

136

137 Several failure databases have been **created** in the last decade. These databases are in the form of tabular data;  
138 they are useful for compiling cases for statistical analysis or in a teaching context. The Association of State Dam  
139 Safety Officials (“Dam Failures and Incidents | Association of State Dam Safety,” n.d.) provides a database  
140 (“Incidents Search | Association of State Dam Safety,” n.d.) that lists a set of incidents and dam failures which  
141 allows the retrieval of basic information about an incident based on search fields such as dam name, incident  
142 mechanisms, failure date, *etc.* Alternately, Bernard-Garcia and Mahdi (2020) record a total of 3,861 cases of  
143 historical dam failures, the largest compilation of such failures recorded to date (17-02-2020). However, the data  
144 and knowledge referring to these dam failures and incidents are stored in the form of reports. This format lacks a  
145 global vision and the explanations of such failures are difficult to exploit with reasoning tools. Although such  
146 database systems handle and provide an easy access to rough massive data, they may not represent knowledge  
147 such as rules, constraints, *etc.* There have since been databases enriched with relational models such as Liu and  
148 Zhou (2008) who developed a relational database for dam safety monitoring systems. Associative research was  
149 carried out to analyse the failure reports and to find similarities between different accidents (Nakao et al., 2008).  
150 This work points out one major difficulty of database analysis: the extraction of general and useful conclusions  
151 from the analysis of many independent cases. Although relational models are widely popular and have been used  
152 since the 1980s for storing and retrieving data (Adeli and Yu, 1993), their dependence on a rigid schema and the  
153 explosive growth of available data result in the loss of their interest and importance (“Comparative analysis of  
154 relational and graph databases | BibSonomy,” n.d.). Indeed, the schema of a relational database (1) makes it  
155 difficult to add new relationships between the objects and thus to efficiently model highly complex networks  
156 connecting all the manipulated objects describing a system in its entirety. Implementing complex systems in  
157 relational databases requires introducing associative tables (also known as join tables) when many-to-many  
158 relationships occur in the model and this is expensive to calculate. To overcome the limits of relational  
159 databases, NoSQL databases provide a very efficient tool for managing a huge volume of complex data,  
160 especially for retrieving relationships between objects. However, NoSQL databases are often schema-less data  
161 models and the unknown general structure of the data especially makes tasks modelling purposes or data analysis  
162 very difficult beyond retrieval data.

163

164 A lack of a formalized language and models in the domain of construction, and notably regarding risk  
165 management, was also pointed out by Mehdizadeh et al. (2012). To overcome the lack of genericity, the use of  
166 ontology (Poli et al., 2010) seems to be an adequate paradigm for structuring the domain of dam systems. In this  
167 sense, the National Performance of Dams Program (“NPDP Dam Dictionary | National Performance of Dams  
168 Program,” n.d.) ([http://npdp.stanford.edu/dam\\_dictionary](http://npdp.stanford.edu/dam_dictionary)) has edited a dictionary allowing the definition of the

169 different elements of dams and their failures. Attempts of ontology have been initiated in the domain of dams  
170 (Anh et al., 2017). Developing a suitable ontology for the domain of dams is of capital importance (1) to share a  
171 common vocabulary in a trans-disciplinary community and (2) to achieve Semantic Interoperability in the field  
172 of dam systems. Although ontology allows users to describe domains and to retrieve information, it is not  
173 capable of simulating or predicting the behaviour of the system while taking uncertainty into account. Ontology  
174 does, however, play a key role in simulation modelling (Benjamin et al., 2006 ; Guizzardi et al., 2015) especially  
175 in disambiguating the terminology of a domain. Ontology and databases complement each other, the ontology-  
176 based model gives a rich representation of data whereas database models are more consistent for querying and  
177 updating (Ramis Ferrer et al., 2021). The trend today is to develop Cloud Collaborative platforms exploiting both  
178 technologies in the same framework allowing companies to exchange information through the web. For instance,  
179 Jeong et al. (2019) developed an interoperable cyber infrastructure platform for bridge monitoring capable of  
180 managing and easily accessing the sensor data and bridge information through NoSQL database, cloud  
181 computing and web services.

182

183 **Thanks to the availability and accessibility of substantial data and advances in computing power**, more recent  
184 approaches stemming from machine learning have started to emerge. Using the neural networks framework,  
185 Danso-Amoako et al. (2012) (*resp.* Wang et al. (2020)) propose a predictive tool of dam failure risk for  
186 sustainable flood retention basins (*resp.* crack opening of concrete dam). Belmokre et al. (2019) tested random  
187 forests and support vector machines for analyzing seepage and collected data in order to predict seepage flow in  
188 concrete gravity dams. Probabilistic graphical models have been investigated to develop models capable of  
189 estimating the likely causes and possible consequences of earth dam failure assigned by probabilities (Morales  
190 Napoles et al., 2014; Ponnambalam et al., 2019). Readers may refer to Allawi et al. (2018) for further details.  
191 The drawback of the mining and learning methods is that they require substantial data.

192

193 The previous detailed discussion shows that the challenge to effectively developing a practical user-friendly tool  
194 capable of capitalizing, diagnosing, predicting and learning in a unified framework using a controlled vocabulary  
195 is still not addressed in the operation of civil engineering infrastructure and particularly in dam systems. To the  
196 best of our knowledge, the methodology exposed in this paper has never been proposed and tested in the  
197 framework of dam systems.

198

### 199 **3. Preliminary notions about Conceptual Graphs (CGs)**

200 CG is a knowledge representation and reasoning formalism based on labelled graphs. They have the advantage  
201 of being easily translated into the terminology of some other approaches in knowledge engineering, such as  
202 RDFS (Resource Description Framework **Schema**) (Yao and Eitzkorn, 2006) and its evolution, the OWL (Web  
203 Ontology Language) (Casteleiro and Des Diz, 2008; Horrocks et al., 2005) mainly applied in connection with the  
204 Semantic Web framework (Shadbolt et al., 2006). It is composed of two parts: the terminological support which  
205 represents basic ontological knowledge and a set of graphs, based on this support, which basically represent facts  
206 (data) expressing factual knowledge. The formalism of CGs allows the development of querying and reasoning  
207 mechanisms to retrieve knowledge without using the language of logic but only using graphs. Logical formulas  
208 and requests may be encoded by means of these graphs which are very interesting to the end-users because this

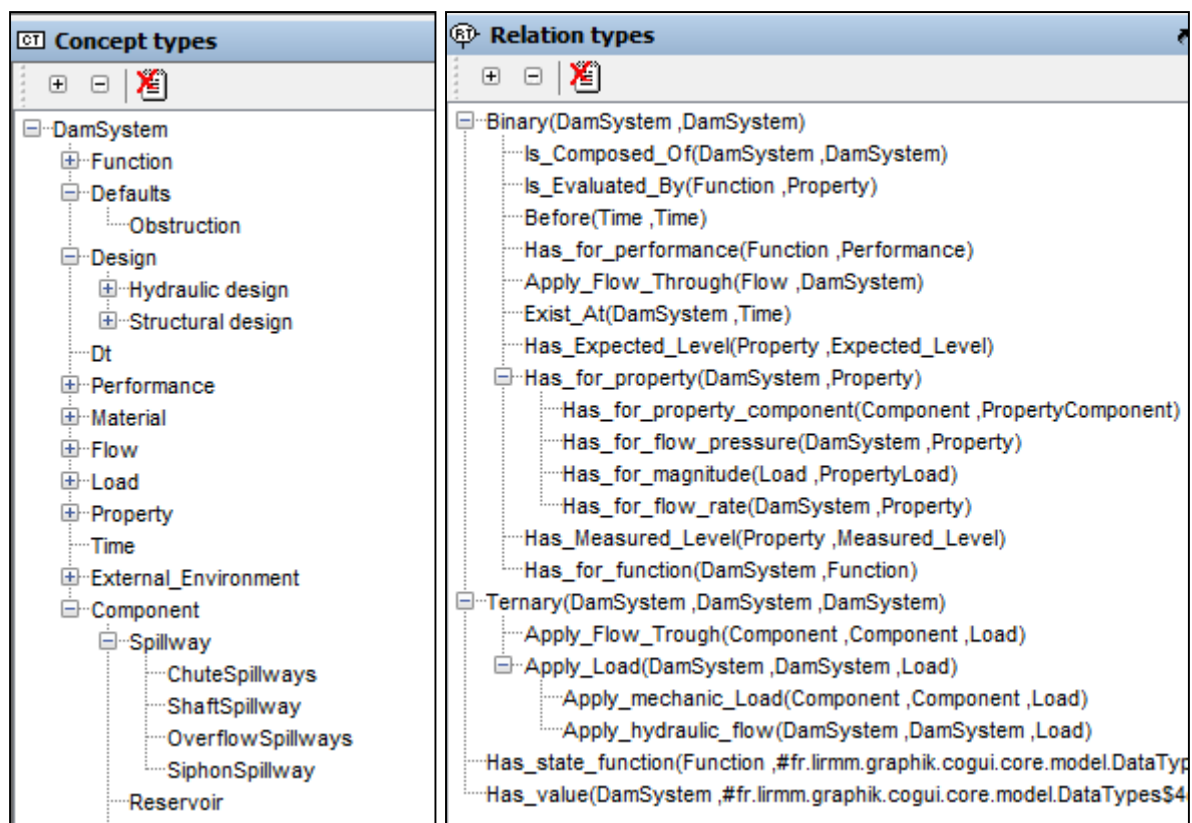


209 makes it possible to explain the reasoning and the results of requests visually in a natural way. The support of  
 210 CGs may then be enriched by rules that express knowledge of the form “if *hypothesis* then *conclusion*” where  
 211 hypothesis and conclusion are both graphs. The graph data management model presented in this paper has been  
 212 implemented in CoGui<sup>2</sup>, a visual conceptual graph editor. CoGui makes possible the manipulation of any CoGui  
 213 objects with a Java-like scripting language, which allows users to create and integrate complex mathematical  
 214 models describing physical behaviours or system functionality. To avoid ambiguity, class, concept, entity, type,  
 215 or category are considered as synonymous terms in this article. Class represents a set of things having a common  
 216 meaning in a domain. The same applies to the terms instance, object, element, individual belonging to a class.

217

### 218 3.1 The terminological support

219 The terminological support consists of a partially ordered set of concepts and a partially ordered set of relations;  
 220 the relations are characterized by their arity which is the number of arguments of the relation. The partial order  
 221 defines a hierarchy relationship allowing a specialization of concepts and relations. For instance Fig. 2 displays  
 222 an extract from the terminological support of Dam systems where the concept “SiphonSpillway” (*resp.* the  
 223 relation “Apply\_mechanic\_flow()”) is a specialization of the concept “Spillway” (*resp.* the relation  
 224 “Apply\_flow()”) that itself is a specialization of the concept “Component” (*resp.* the relation “Ternary()”). The  
 225 relation “Has\_Default(Component,Defaults)” takes two arguments corresponding to the concepts “Component”  
 226 and “Defaults” describing that “a component has a default”.



227

228 **Figure 2** : An extraction of a terminological support: an example of the hierarchy of concept types and relation

229

types, Dt refers to a period of time.

<sup>2</sup> <http://www.lirmm.fr/cogui/>



230

### 231 3.2 Basic graph

232 Generic knowledge may be represented by means of a **basic graph**, based on the terminological support that is a  
233 bipartite graph composed of:

- 234 • concept nodes labelled by a pair  $[C:c]$ , where  $C$  is a concept type and  $c$  is called the marker of this  
235 node. Either this marker is a specific individual name, that is  $c$  is an instance of the concept  $C$  (e.g  
236  $[DamSystem:Grande-Dixence-dam]$  means that *Grande-Dixence-dam* is an individual of the  
237 *DamSystem* concept; it is a concrete gravity dam in Switzerland); otherwise this marker is the generic  
238 marker, denoted by  $*$ , if the node refers to an unspecified individual in the knowledge base (e.g  
239  $[DamSystem : *]$  means there exists an individual of type *DamSystem* in the knowledge base).
- 240 • relation nodes labelled by a relation  $r$  expressing relationships between concept nodes. The number  
241 of incident edges (*i.e.* the number of edges to which it is connected) is equal to the arity of the  
242 relation. CoGui software offers the possibility of managing specific data types (string, integer, float,  
243 boolean) by means of binary relations allowing the integration of physical phenomena inside rules by  
244 means of scripts (see below).

245

### 246 3.3 Facts

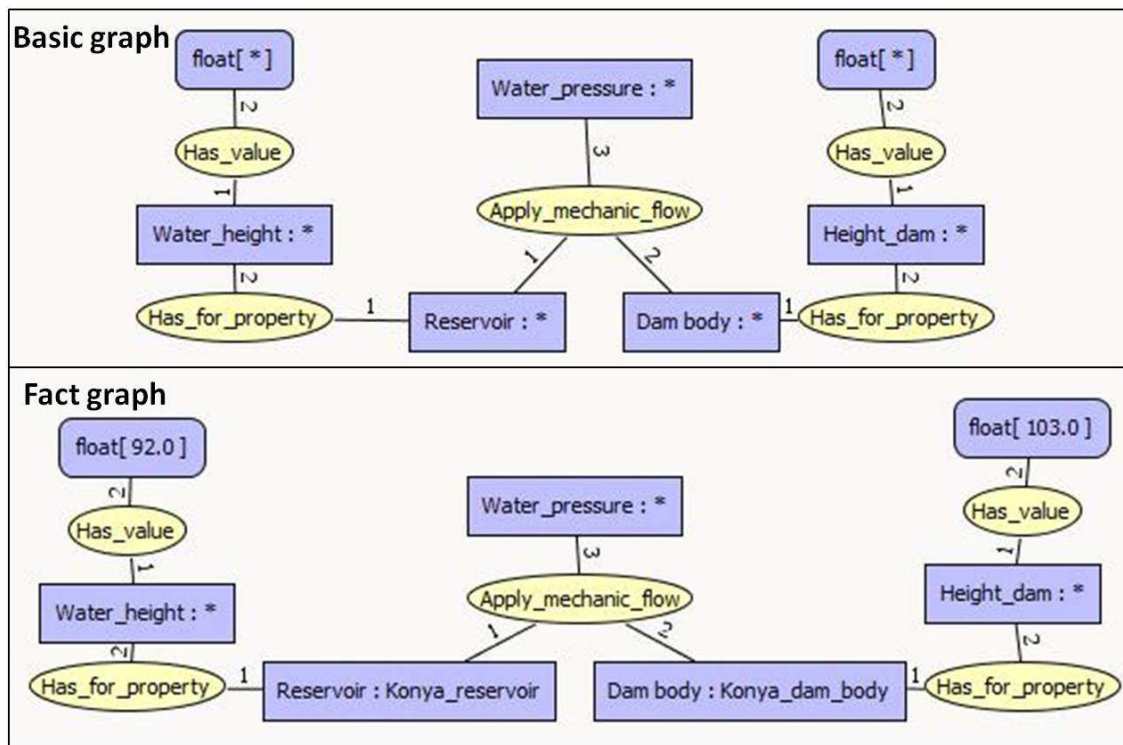
247 Basic graphs may be then used to generate factual knowledge called **Facts (or fact graphs)**. Classically, concept  
248 nodes are represented by rectangles and relation nodes by ovals. Figure 3 displays a simple example of a basic  
249 graph describing the bodies of dam associated with its reservoirs. The basic graph means that any reservoir  $R$  of  
250 type *Reservoir* with a level water  $WH$  of type *Water\_height* associated with a float value  $wh$  applies a water  
251 pressure  $WP$  on the dam body  $DB$  that has a height  $HD$  of value  $hd$ . From this basic graph, facts may be  
252 instantiated as for instance the Konya dam, the largest completed hydroelectric power plant in India, by means of  
253  $R=Konya\_reservoir, wh=92$  meters,  $DB=Konya\_dam\_body$  and  $hd=103$  meters (see fact graph in Figure 3).

254

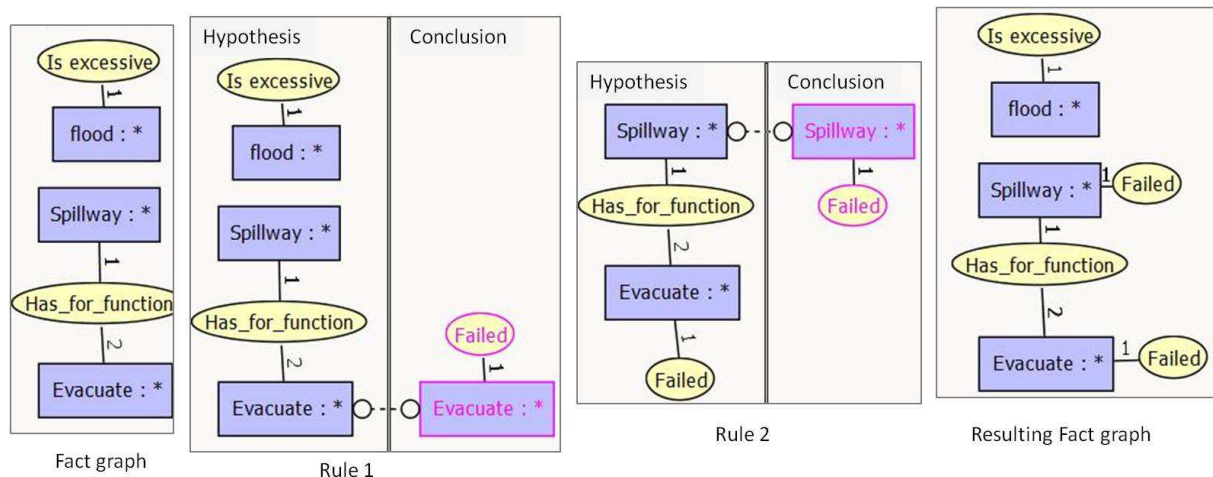
### 255 3.4 Rules

256 Different kinds of reasoning may be graphically defined in the framework of conceptual graphs namely applying  
257 inference rules or contextual reasoning (*i.e.* find a current situation having similar features with already  
258 encountered situations). **Rules** express knowledge of the form “if *hypothesis* then *conclusion*” where hypothesis  
259 and conclusion are both graphs sharing common nodes. Intuitively, when the hypothesis graph is found in a fact  
260 graph, then the conclusion graph can be added to this fact. A rule  $R$  is applicable to a fact graph  $G$  if there exists  
261 an injective homomorphism (also called injective projection) from its hypothesis to  $G$ , *i.e.* this projection consists  
262 of knowing whether the hypothesis graph is present in  $G$ . Then the application of  $R$  on  $G$  according to the  
263 projection produces a new graph fact obtained from  $G$  by adding the conclusion. For instance, Figure 4 displays  
264 the result of the use of two rules applied to a fact graph. The fact graph expresses that there is an excessive flood  
265 in the environment of a spillway which has for function to evacuate water. The first rule formally says that “for  
266 any flood  $f$ , spillway  $s$  and evacuate  $e$ , if  $f$  is excessive and  $s$  has for function  $e$ , then  $e$  is failed. There is one to  
267 one correspondence between the concept node  $[Evacuate: *]$  in the hypothesis and with the concept node

268 [Evacuate: \*] in the conclusion. These two nodes linked by a relation called co-reference (symbolized by dashed  
 269 edges and circle vertices in Fig. 4) refer to the same entity.  
 270

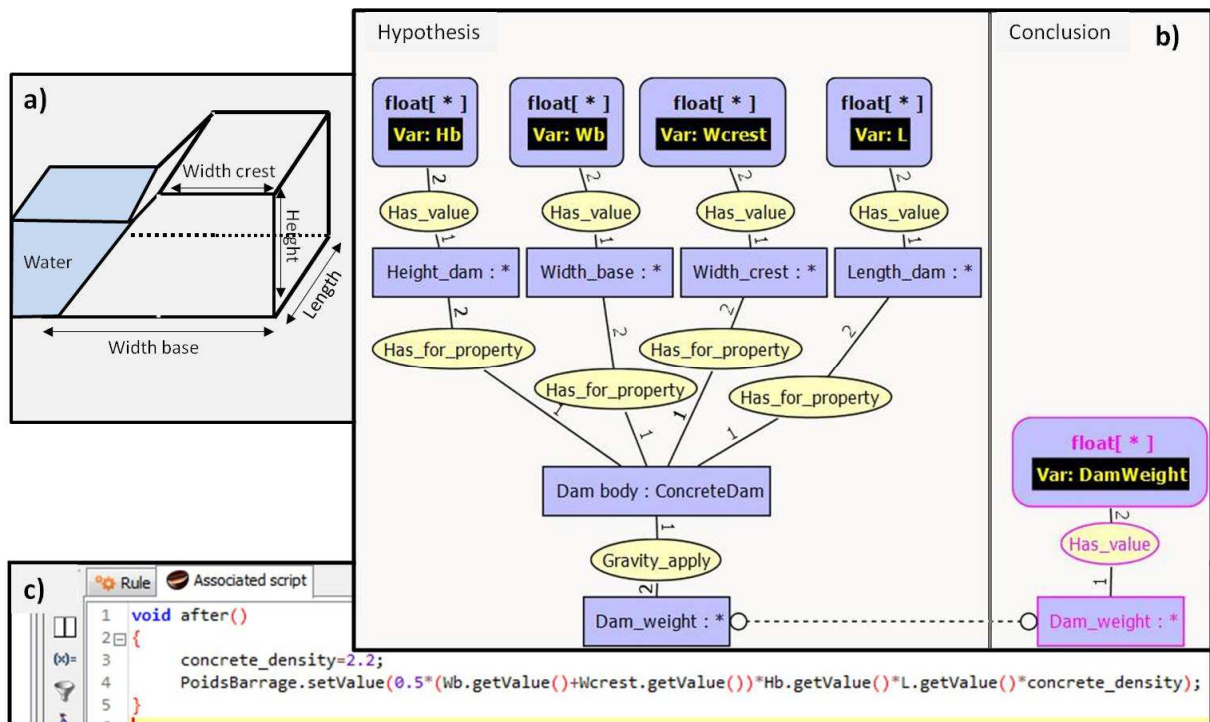


271  
 272 **Figure 3** : Example of a specific fact graph instantiated from the basic graph



273  
 274 **Figure 4** : Example of two rules applied to a fact graph

275 Concept graph rules may be extended in the CoGui software by using a Java-like scripting language allowing  
 276 users to add computations. Figure 5.b displays the graph rule associated with its script in Fig.5.c allowing users  
 277 to compute, as the result of the calculation process, the weight of a concrete dam schematized in Fig.5.a.  
 278



279

280 **Figure 5 :** Example of a script (c) allowing users to compute the weight of a concrete dam (a) that is associated  
 281 with the graph rule (b)

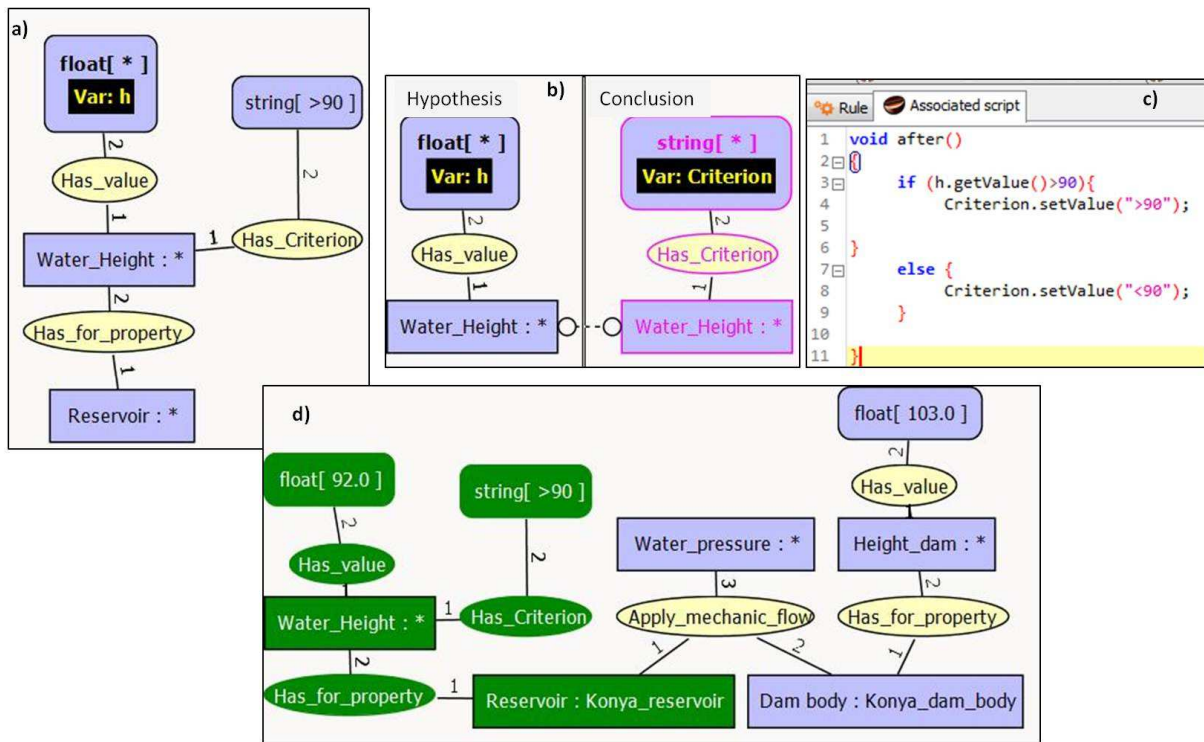
282 As in rules, a query-answering mechanism may be developed in the framework of CGs by using (1) the relation  
 283 of projection from graphs to graphs and (2) the definition of requests by means of graphs. Let  $B$  be a knowledge  
 284 base composed of a set of fact graphs, *e.g.*, the fact about the Konya dam in Figure 3. Elements in  $B$  answering a  
 285 query  $Q$  are intuitively present in  $Q$ . Query-answering mechanism and inferences rules may be coupled. For  
 286 example, the request graph (see Fig. 6.a) requires searching, in the knowledge base, all reservoirs with a water  
 287 height over 90 metres, and Figure 6.d displays the answer graph. The idea is (1) to apply the rule in Fig. 6.b  
 288 associated with its script in Fig. 6.c to all facts in the knowledge database creating new facts extended with the  
 289 criterion “>90” or “<90” and (2) to identify all new fact graphs containing the request graph in Fig.6.a. Figure 6.d  
 290 shows that the Konya reservoir answers this request.

291

## 292 4. Formal graph-based knowledge representation of dam systems

### 293 4.1 The core ontology of Dam systems

294 The ontology supports the description of all key concepts (entities, variables and attributes) which play a role in  
 295 the dam systems (and, with a reduced scope, in the structural and functional performance of the dam). It also  
 296 supports the model by explaining how they can be consistently described at different scales (*i.e.* levels of details)  
 297 and what their relations are. This section exposes the terminological support related to dam systems and dam  
 298 failures required to build a generic model of dam systems for the implementation of a graph-based knowledge  
 299 database of dam systems. It is difficult to propose a unique classification of dams. Indeed, dams may be  
 300 classified by several aspects for instance based on shape, height, construction material or type of use, etc. The  
 301 proposed model will make it possible to free oneself from any classification and will allow an analysis from  
 302 different angles (*i.e.* design, function, performance, etc).



304

305

306 **Figure 6 :** Example of a query-answering in the form of a graph (d) coupling a request graph (a) with an  
 307 inference rule (b) associated with a script (c).

308

309 A system “is a set of entities with relations between them” (Langefors and Dahlbom, 1995) ; it will be  
 310 considered as the top level of the concept type hierarchy. A dam system is a system and defined according to its  
 311 structural components, its functions and its environment. At each level of decomposition of the system, structural  
 312 components perform functions that contribute to the global functions of the dam system. **The building of**  
 313 **ontology is based on a Middle-out strategy which is a combination of the Top-down and Bottom-up approaches**  
 314 **(Aminu et al., 2020). By relying on the dictionary of National Performance of Dams Program (“NPDP Dam**  
 315 **Dictionary | National Performance of Dams Program,” n.d.), relevant generic concepts and relations have been**  
 316 **collected by domain experts elicitation. These top level concepts and relations have been refined by means of**  
 317 **more specific concepts and relations manually extracted from a corpus of Dam failure cases. This extraction**  
 318 **process will be able to be automated by using ontology learning tools (Konys, 2019) allowing ontology designer**  
 319 **to support the building process. A terminological support has then been developed and it is composed of**

320

### 321 Concepts:

- 322 • **Component** is associated with all components that compose a dam system such as spillway, reservoir,  
 323 dam body, foundation.
- 324 • **Function** is what the system or component is intended to do. It is specified by (1) mechanical functions  
 325 such as sliding stability, (2) technical functions such as control flood and (3) useful functions such as  
 326 recreational activity, energy production.

- 327 • **Design** is associated with the type of design of dam such as embankment, arch, buttress dams *etc.*
- 328 • **Performance** is the capacity of a system or component to fulfil its function as for instance the
- 329 performance of spillway evacuation is its capacity to evacuate water.
- 330 • **Expected level** represents the level of performance designed to satisfy the function of a component as
- 331 for instance the tolerated increase of the drainage flow
- 332 • **Measured level** is the quantitative measure of the performance level of a component that indicates the
- 333 actual degree to which it performs the function as for instance the height of water in the reservoir.
- 334 • **Property** concerns all attributes, properties and characteristics allowing the description of a component,
- 335 a function, an environment, a load, a flow such as the geometrical shape of dam body, the intensity and
- 336 the duration of rainfall, the level of reservoir.
- 337 • **Load** characterizes the load transfers that take place in the dam system between components. It is
- 338 specified into horizontal loads such as horizontal water pressure from the reservoir to the dam body and
- 339 vertical load such as the uplift pressure.
- 340 • **Flow** characterizes the flow transfers that take place in the dam system between a flow outside the dam
- 341 system and the components such as overflow, seepage, spillway discharge, *etc.*
- 342 • **Material** represents any material which is used for construction and operation of a system such as water,
- 343 tailings, concrete, soil, rock.
- 344 • **Time** represents the notion of time.
- 345 • **External environment** represents all factors outside of the dam system that interact with it such as
- 346 human activity, weather, temperature.
- 347 • **Failure** is defined as an unacceptable performance of a structure to perform its function.

348

349 **Relations:**

- 350 • **Is\_composed\_of** is a binary relation that links the dam system with its components.
- 351 • **Has\_for\_function** links the component to its function.
- 352 • **Has\_value** links a property to its value of float type. For instance [Reservoir\_area: \*]-<sup>(1)</sup>-Has\_value-
- 353 <sup>(2)</sup>[Float: \*].
- 354 • **Has\_for\_material** links a component to its material of string type. For instance [Dam\_body: \*]-<sup>(1)</sup>-
- 355 Has\_for\_material-<sup>(2)</sup>-[String: 'concrete'].
- 356 • **Is\_Evaluated\_By** is a binary relation that links a function with the property that allows the function to
- 357 be evaluated as for instance the function “to evacuate”, associated with the component “spillway”, may
- 358 be evaluated by the property : the evacuated water flow.
- 359 • **Exist\_at** is a binary relation linking all types of concepts to time that can change over time according to
- 360 different events or phenomena.
- 361 • **Has\_Measured\_Level** (*resp.* **Has\_Expected\_Level**) is a binary relation linking a measured value (*resp.*
- 362 expected value) of quantitative properties. For instance, the evacuated water flow, that evaluates the
- 363 function “evacuate” of spillway, has a measured level and an expected level.
- 364 • **Has\_for\_performance** is a binary relation that links the function of a component to its performance.
- 365 • **Has\_for\_property** is the binary relation that links the properties of any concepts. This relation may be
- 366 declined according to the manipulated concepts such as the relation **Has\_for\_flow\_rate** (*resp.*

- 367        **Has\_for\_flow\_pressure, Has\_for\_load\_magnitude**) which specifies the rate of the overflow (*resp.* the  
368        pressure of the overflow and the magnitude of the horizontal water pressure).
- 369        • **Has\_for\_probability** is a binary function that assigns a probability to an event.
  - 370        • **Apply\_load** is a ternary relation that describes the transfer of a load on a component to another  
371        component. This relation will be subdivided into two sub-relations: **Apply\_mechanic\_load** and  
372        **Apply\_hydraulic\_flow**. For instance, earthquake applies an earthquake hydrodynamic load to reservoir;  
373        reservoir applies a mechanical load namely a pressure to the dam body.
  - 374        • **Apply\_Flow\_Through** is a binary relation that links a flow to a component such as an overflow to the  
375        dam body.
  - 376        • **Before** is a binary relation between two time concepts that represents a sequence of events or state  
377        changes in a temporal order.
  - 378        • **Has\_state\_function** is a binary relation that describes the state of the function of component.

379

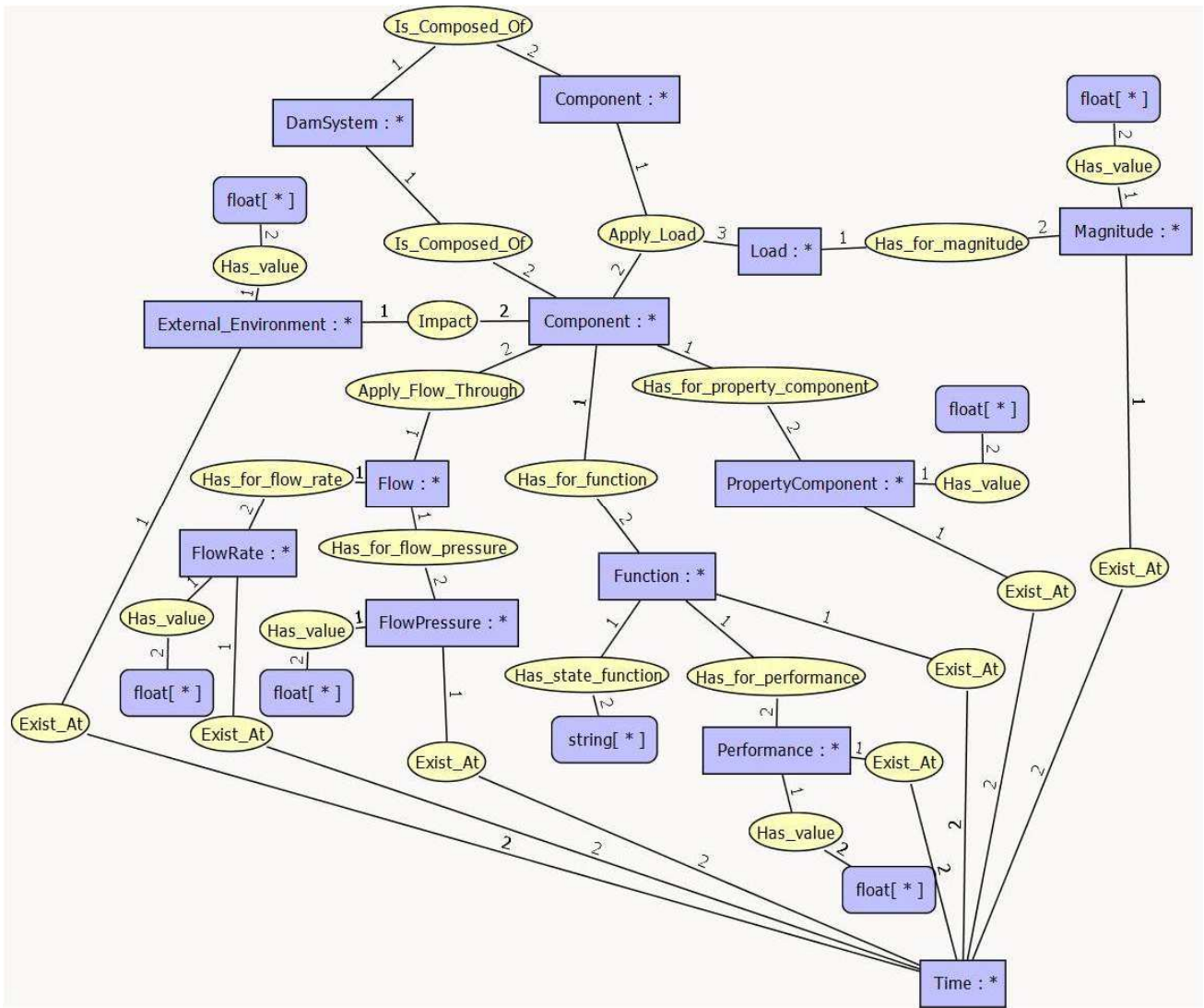
380        For the sake of clarity of the paper, only the first levels of the core ontology are described in this section. Fig. 2  
381        shows a part of the hierarchy view of concepts and relations stemming from the developed terminological  
382        support of dam systems.

383

#### 384        **4.2 Basic graph representing dam systems**

385        The core ontology allows the definition of a basic graph enabling users to represent any kind of dam as an  
386        assemblage of load-bearing components that interact with each other to perform the designated function of the  
387        system. Figure 7 shows the basic skeletal graph corresponding to a high level representation of dam systems. It  
388        means that, for any time  $t$ , any dam system  $ds$  of type *DamSystem* is composed of components  $c$  of type  
389        *Component*. Any component  $c$  (1) is impacted by an external environment  $ee$  of type *External\_Environment*, (2)  
390        has properties  $p$  of type *PropertyComponent* and functions  $f$  of type *Function*. Any function  $f$  has performance  
391        criterion  $perf$  of type *Performance* that are estimated by means of the properties of components associated with  
392        their modes of degradation. The interaction between components is described through load  $l$  of type *Load* that  
393        has a magnitude  $m$  of type *Magnitude* associated with a value  $v$  of type *float*. Any flow  $f$  of type *Flow* has a flow  
394        rate  $fr$  of type *FlowRate* associated with a value  $vr$  and a flow pressure  $fp$  of type *FlowPressure* associated with a  
395        value  $vp$  that passes through a component. Each component may have several functions and properties and it is  
396        sufficient to duplicate this skeleton for each component in order to have a whole description of dam systems.  
397        Each magnitude, flow rate, flow pressure, performance could be either measured or computed by means of  
398        physical laws and modes of degradation. The basic skeletal graph may be extended by a specification allowing  
399        users to describe components, functions, performances at finer levels. For instance, an embankment dam is a  
400        dam system that is composed of a dam body that may be composed of upstream and downstream shells, a  
401        permeable membrane and a drain (see Fig. 8). The capacity of the dam body to resist internal erosion will depend  
402        on the permeability function, the drainage function and the filtration function (see Fig. 8). The core ontology  
403        may then describe the complexity of components at different levels of interaction with others and their  
404        environment. Its use, at a given level, consists in identifying adequate components, functions and relationships.





405

406

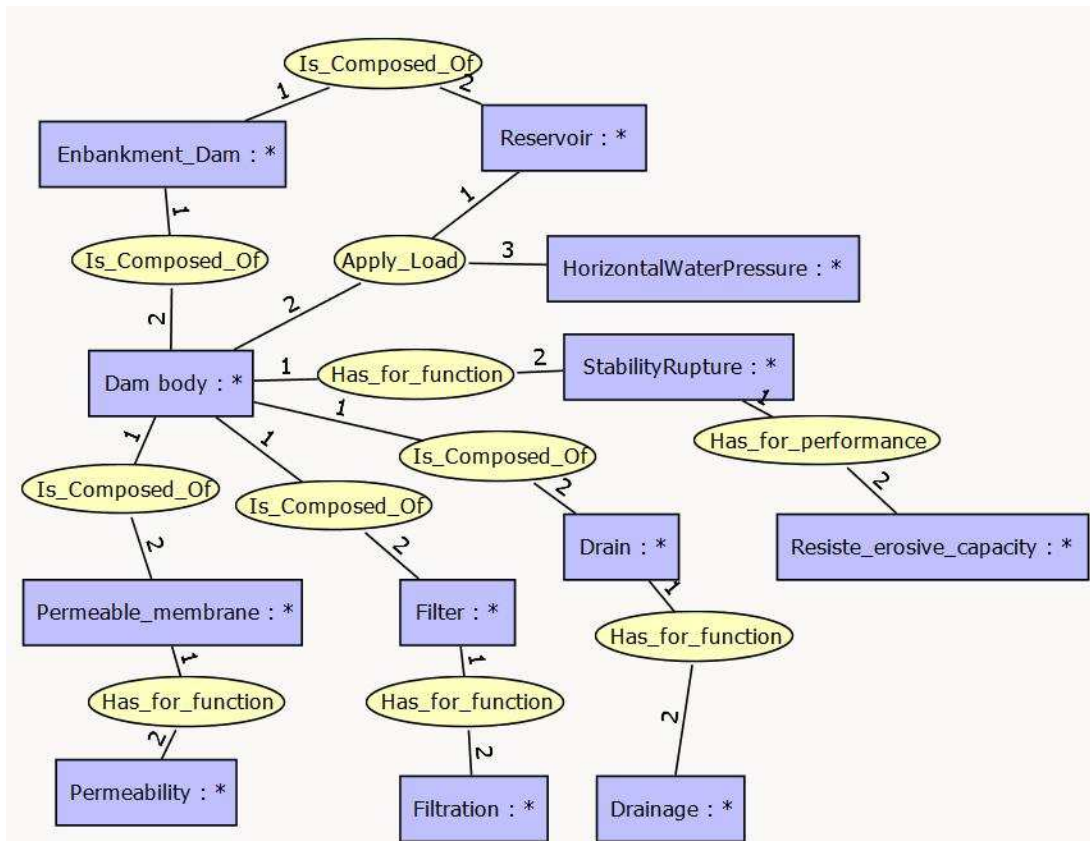
**Figure 7 :** Section of the basic skeletal graph representing dam systems using the core ontology

407

408

409

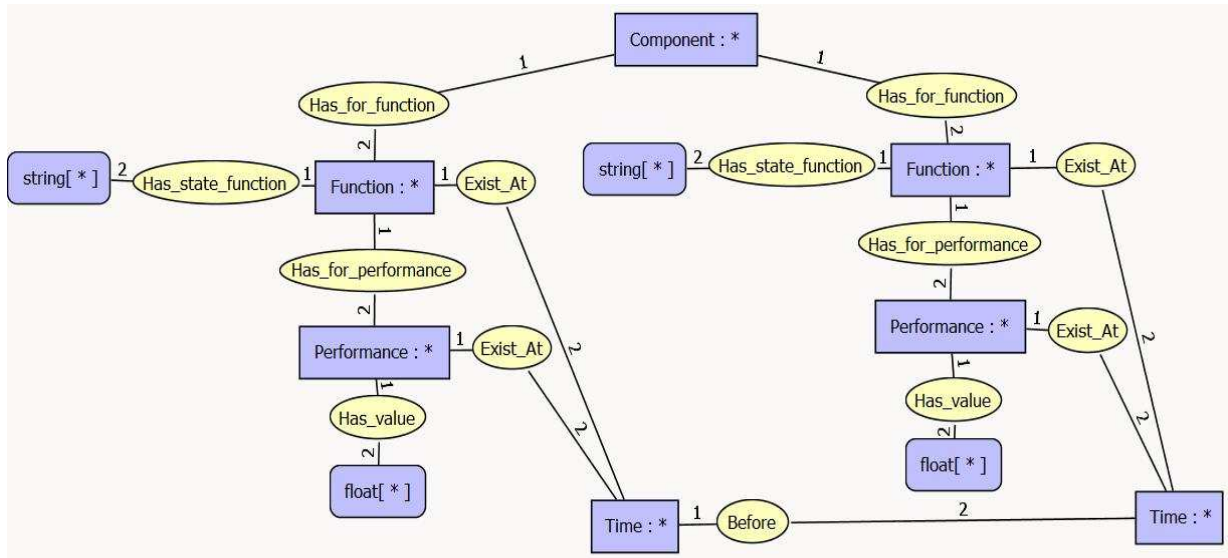




410  
411

412 **Figure 8** : Section of a specification of the basic skeletal graph representing embankment dam system

413 The description of failures or degradation processes must include time (essential for detecting failure  
 414 precursors); with the concept *Time*, the basic skeletal graph may be extended by using the binary relation *Before*  
 415 to describe dam systems over the time. For instance, Fig. 9 displays a section of the basic skeletal graph  
 416 representing one functional state of a component associated with its performance over two time steps. It means  
 417 that there exists a component  $c$  that has a functional state  $f_1$  (resp.  $f_2$ ) with its performance  $p_1$  (resp.  $p_2$ ) at time  $t_1$   
 418 (resp.  $t_2$ ). By unrolling the two time steps over  $n$  time steps, we may have a description of dam systems over  
 419 time.



420

**Figure 1** Section of the basic skeletal graph representing the functional state of a component over two time steps

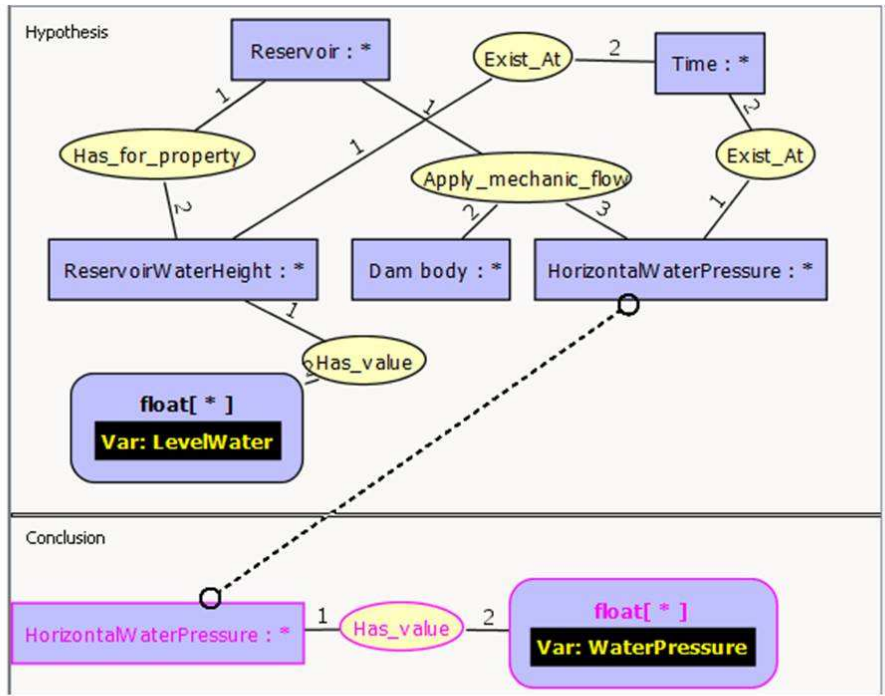
421 **4.3 Performance estimation of component functional states**

422 The functional states of components are assessed by their performances. These performances can be estimated  
 423 by means of decision rules associated with mathematical models capable of simulating physic-chemical  
 424 degradation modes linked to erosion, dissolution phenomena, sliding, overturning, shearing, *etc.* For the sake of  
 425 clarity, we only present in the following a few simplified reasoning graphs representing mechanism, phenomena,  
 426 etc in a macroscopic view. These simplified models must not be used to assess dam safety. However, it will be  
 427 possible to couple existing complex and more accurate numerical models with our model. The aim here is not to  
 428 be exhaustive but to illustrate the approach. For example:

429

- 430 i. The water pressure load over the time  $P_{wh}(t)$  is applied to the dam body can be estimated by  $P_{wh}(t)=$   
 431  $\gamma \cdot h(t)^2/2$  where  $\gamma$  corresponds to the density of water and  $h(t)$  corresponds to the height of water inside  
 432 the reservoir. This estimation may be integrated in a graph rule by using the Java-like scripting  
 433 language in the CoGui software (see Fig. 10).

434



```

1 void after()
2 {
3     omega_water=10;
4     WaterPressure.setValue(LevelWater.getValue()*LevelWater.getValue()*0.5*omega_water);
5 }

```

435

436

**Figure 10:** Graph rule associated with its script to estimate the horizontal water pressure

437

438 ii. The capacity to resist external erosion for a dam body, in the case of overflow, allows the assessment  
 439 judgement of the state of one dam body function that is to resist external erosion. It can be evaluated by  
 440 means of a depth of breach inside the dam body. It depends on the erodibility of the dam body, the  
 441 width of crest and the overflow level associated with its throughput. We can for instance use the  
 442 following very simple rule :

443

444 If  $W_c(t) \geq 0$

445     ▪  $W_c(t+1) = \max(0, W_c(t) - e.H_{flow}(t) \times \Delta_t)$

446 Else (Eq.1)

447     ▪  $W_c(t+1) = 0$

448     ▪  $H_{breach}(t+1) = H_{breach}(t) + e.H_{flow}(t) \times \Delta_t$

449

450 where  $W_c(t)$  (*resp.*  $e$ ,  $H_{breach}(t)$ ,  $H_{flow}(t)$ ,  $\Delta_t$ ) corresponds to the width of crest (*resp.* the erodibility factor,  
 451 the height of breach, the height of overflow and the duration of overflow). This rule means that the  
 452 width of crest  $W_c(t)$  may be reduced to zero only if there exists an overflow  $H_{flow}(t)$  during  $\Delta_t$ . The  
 453 breach which appears from the width of crest is null and its depth increases according to the overflow  
 454 level  $H_{flow}(t)$  associated with its  $\Delta_t$ . As mentioned previously, the breach depth may be estimated by  
 455 using a graph rule associated with a script implementing the above rule. Of course, more complex

456 models for dam breaching can be implemented, depending on the material properties and the shape of  
457 the dam section (Peter et al., 2018, Zhong et al., 2021).

458  
459 The performance of the stability function against the sliding of the dam may be estimated by a Boolean  
460 factor that is 1 if the friction angle (inclination angle that a considered sliding plane can have  
461 before it starts to slide) is lower than a limit and 0 otherwise. The friction angle, denoted  $\alpha(t)$  may be  
462 estimated by:

$$463 \alpha(t) = \text{Arctan}(P_{wh}(t) / (P_{sw}(t) - P_{up}(t))) \times 180/\pi \quad (\text{Eq.2})$$

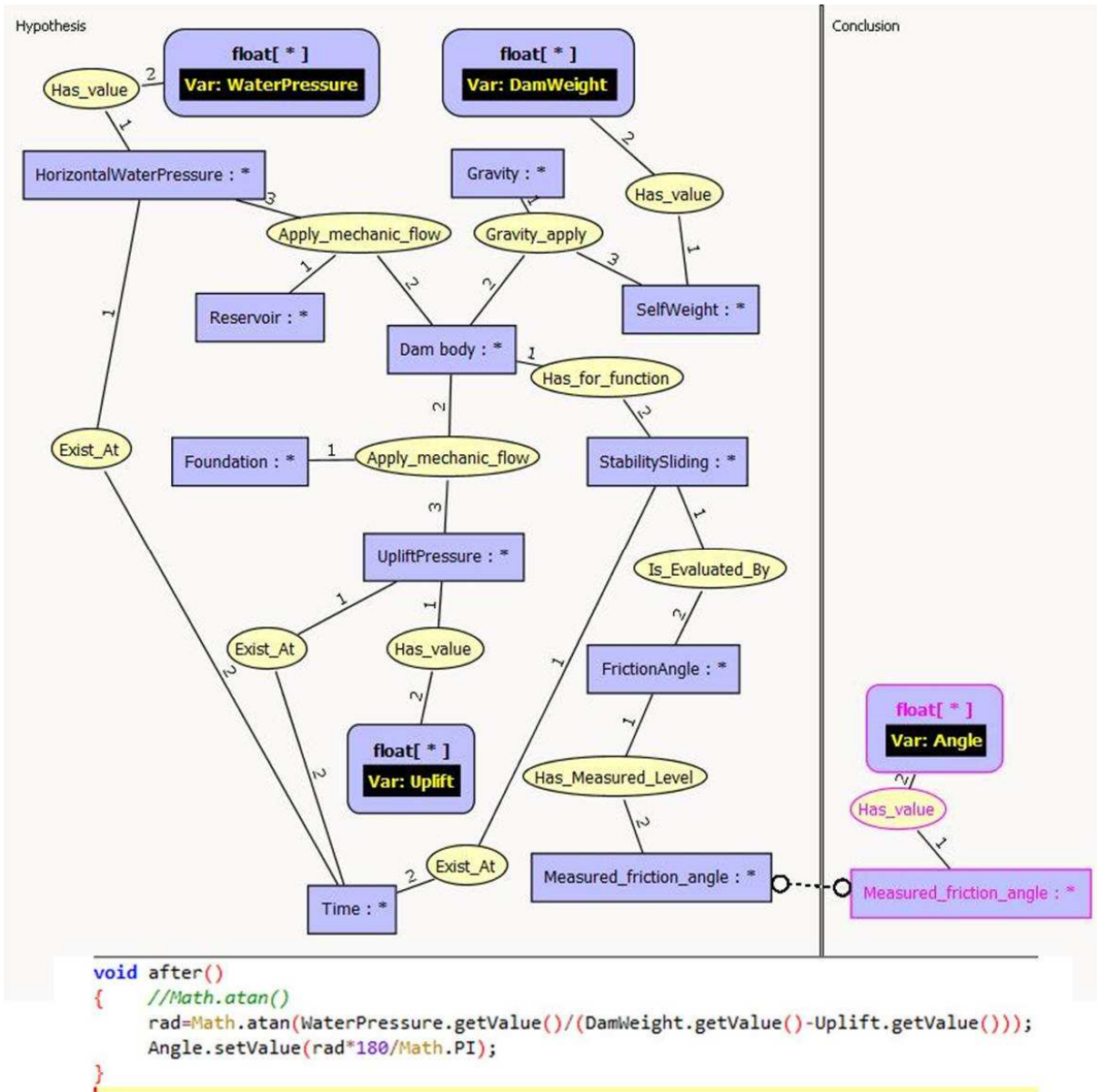
464  
465 where  $P_{sw}(t)$  is the self-weight of dam body,  $P_{up}(t)$  is the uplift pressure and  $P_{wh}(t)$  is the horizontal  
466 water pressure. This rule is depicted by means of the graph in figure 11.

467  
468  
469 iii. The performance of spillway, at a time step, may be estimated by its capacity CAP\_EVAC to evacuate  
470 water :

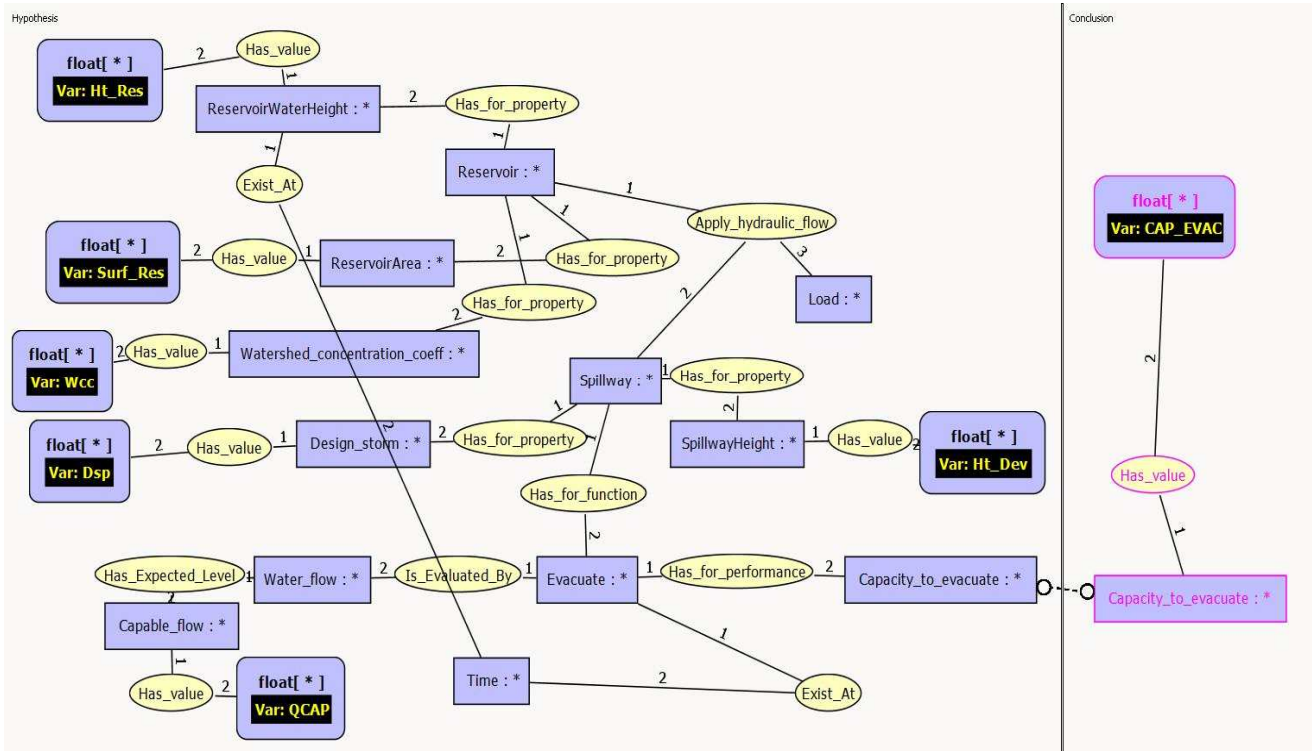
$$471 \text{CAP\_EVAC} = \text{QCAP} / (\text{Dsp} \times \text{Wcc} \times \text{Surf\_Res}) \quad (\text{Eq. 3})$$

472  
473 where QCAP (resp. Dsp, Wcc and Surf\_Res) is the measured flow (resp. the design storm project, the  
474 ratio watershed area/reservoir area and the surface of reservoir). The function of spillway may be then  
475 considered as failed if  $\text{CAP\_EVAC} < 1$ . This rule is depicted by means of the graph in figure 12.

476  
477  
478  
479  
480



482 **Figure11 :** Graph rule associated with its script to estimate the horizontal water pressure



484 **Figure 12:** Graph rule to estimate the capacity of spillway to evacuate water

485

## 486 5. Uses of the graph-based knowledge model

487

488 The model can be used for four purposes: (1) to store a database of dam systems either in operation or having  
 489 experienced a failure; (2-3) to analyze the condition of a structure and either estimate or foresee the associated  
 490 risks and (4) to identify the likely causes or reasons of failures when they occur. In the first use, the user will be  
 491 able to implement a database of dam systems and their environments. In the second and third use, the user,  
 492 through the tool, will be able to either assess the states of current dam systems or predict different possible  
 493 failure scenarios. Lastly, the user will be able to highlight the possible causes of some past failures, in order to  
 494 draw lessons.

495

496

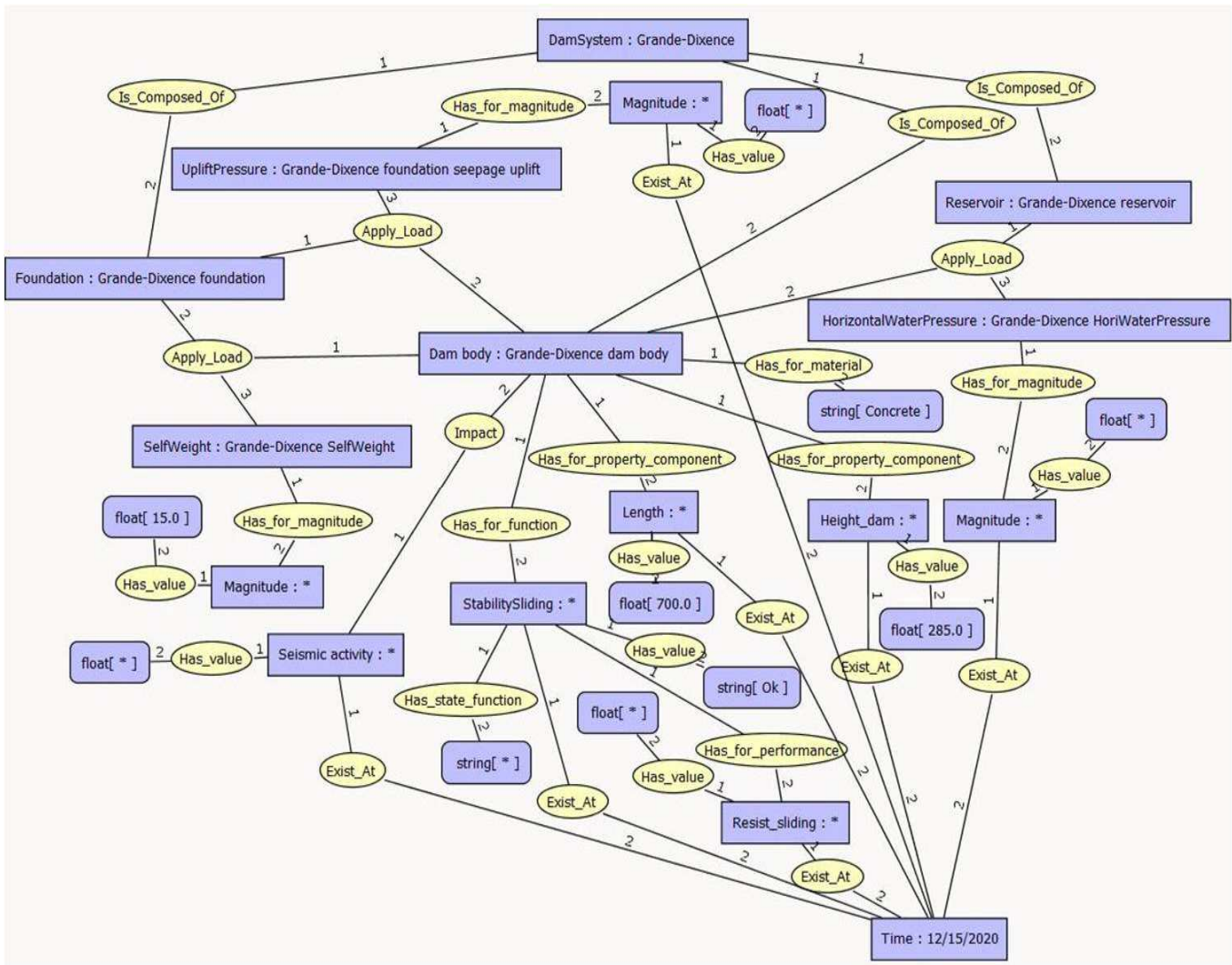
### 497 5.1 Informing the fact graph database

498

499 By using the generic graph in Fig.7, the creation of the fact graph database is illustrated by the example of the  
 500 instantiation of the Grande-Dixence dam located in the canton of Valais in Switzerland on the Dixence river and  
 501 the failure of the Malpasset dam which is an arch concrete dam on the Reyran River in the south of France.  
 502 Figure 13 displays a section of the representation of the Grande-Dixence dam (the tallest concrete gravity dam).  
 503 That is the *Grande-Dixence* is an individual of concept *DamSystem* that is composed of three components  
 504 namely the *Grande-Dixence dam body* (resp. the *Grande-Dixence foundation*, the *Grande-Dixence reservoir*)  
 505 that is of type *Dam body* (resp. *Foundation* and *Reservoir*). The dam body of the Grande-Dixence dam has a  
 506 height of 285 metres and a length of 700 metres at the date of 15/12/2020. It applies a load of  $1.47 \times 10^{11}$  N over



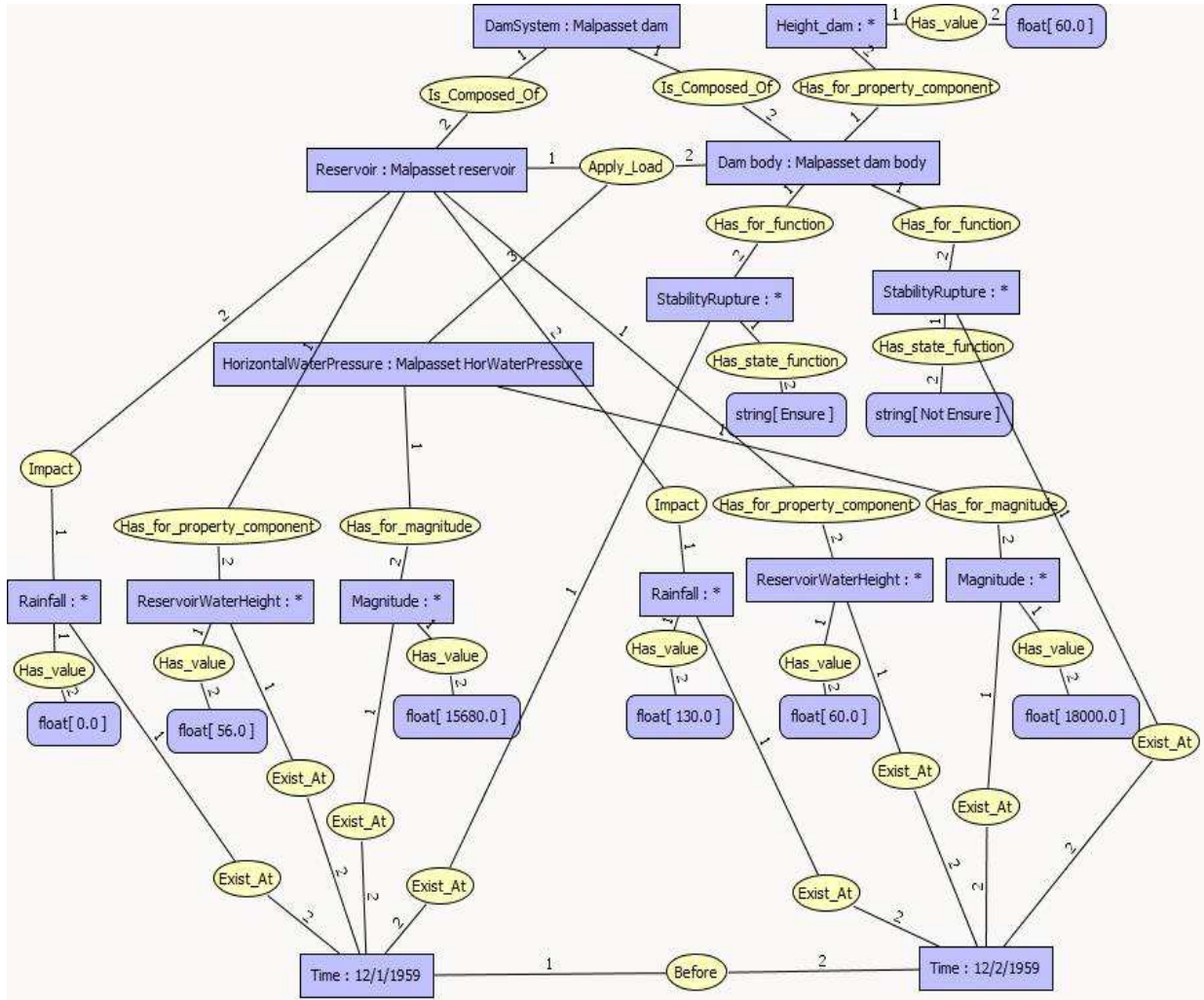
507 the foundation. One of the functions of the dam body is to ensure the sliding stability *Resist\_sliding* which  
 508 depends on the magnitude of foundation seepage uplift load, the water pressure load and the self-weight load.  
 509 This estimation may be integrated under the form of a rule coupled with a Java script as explained in section 3.  
 510  
 511 Figure 14 represents a section of the functional state of the Malpasset dam body over two time steps. Malpasset  
 512 dam was breached on December 2, 1959 partially due to heavy rainfall. This resulted in an increase of reservoir  
 513 load water on the dam body that implied an increase of dam weight on the foundations. The generated uplift  
 514 pressures and the low shear strength along a fault led to the collapse of foundation and the breach of the dam  
 515 body. Figure 14 reveals that the quantity of rain during 24 hours was 130 mm that implied an increase of load  
 516 water (*resp.* water level) from 15680 kN tons to 18000 kN tons (*resp.* from 56 m to 60 m) between the 12/1/1959  
 517 and 12/2/1959. The water level in the reservoir then reached the height of the dam body. However, the failure  
 518 stemmed from uplift pressures: the water present in the foundation could not be evacuated due to the poor  
 519 mechanical characteristics of the rock foundation. This led to a sudden failure of the foundation and  
 520 consequently of the dam itself. Based on the basic graphs presented previously, it is possible to implement a  
 521 graph dam database to store information about operating dams and dams having a known failure.  
 522



**Figure 13 :** Section of a representation of the Grande-Dixence dam using the basic skeleton graph in Fig.7



523 The graph database will be enriched and updated with the existing database (“Incidents Search | Association of  
 524 State Dam Safety,” n.d.) (Bernard-Garcia and Mahdi, 2020). Missing data or missing knowledge may be taken  
 525 into account by means of the generic marker \* (see section 3) which refers to an unspecified or unknown  
 526 individual in the knowledge base. Since each dam implementation may be incomplete and updated later, the  
 527 graph database can thus be implemented by any stakeholders such as experts, teachers, technicians, owner, etc.  
 528



529  
 530 **Figure 14 :** Section of the graph representing the functional state of the Malpasset dam body over two time  
 531 steps.

532 **5.2 Diagnostic and prediction**

533  
 534 The aim of this subsection is to highlight the consistency of the model through its predictive character and that  
 535 the model may potentially describe complex behaviours by using a common formalism. We consider a fictitious  
 536 simplified embankment dam system where the properties of dam body, reservoir, and spillway are summarized  
 537 in table 1. Erodibility is a simplified parameter for this case study that describes the vertical and horizontal  
 538 erosion of mass in metres by days; its value is underestimated in these examples for the sake of demonstration.  
 539 Watershed concentration coefficient is a surface ratio watershed area/reservoir area and describes a coefficient of  
 540 watershed water concentration meaning that 1 cm of rainfall in the drainage basin leads to an increase of 50 cm

541 of water in the reservoir. The spillway could be either obstructed or not, according to an occurrence probability  
 542 each day and the obstruction is associated with an intensity coefficient, lying within [0,1].

543

544 The predictive character of the model is tested and illustrated according to three different scenarios:

545

546 i. The dam is confronted with rainfall and remains operational thanks to the ensured function of the  
 547 spillway.

548 ii. The dam system is confronted with strong rainfall leading to a flood; the function of the spillway is  
 549 ensured but it does not have the capacity to sufficient evacuate water leading to an overflow and then  
 550 the erosion of the dam.

551 iii. The dam system is confronted with rainfall and an obstruction of the spillway leading to an overflow  
 552 but the stopping of rainfall and a clearing of the spillway will allow the dam to partially recover all its  
 553 functions.

554

**Dam Body properties**

Height (m)	Base Width (m)	Crest width (m)	Material	Tolerated overflow (m)	Erodibility
30	110	10	embankment	0	3m×day <sup>-1</sup>

**Reservoir properties**

Height (m)	Surface area (m <sup>2</sup> )	Watershed concentration coefficient (-)
24	300 000	50

**Spillway properties**

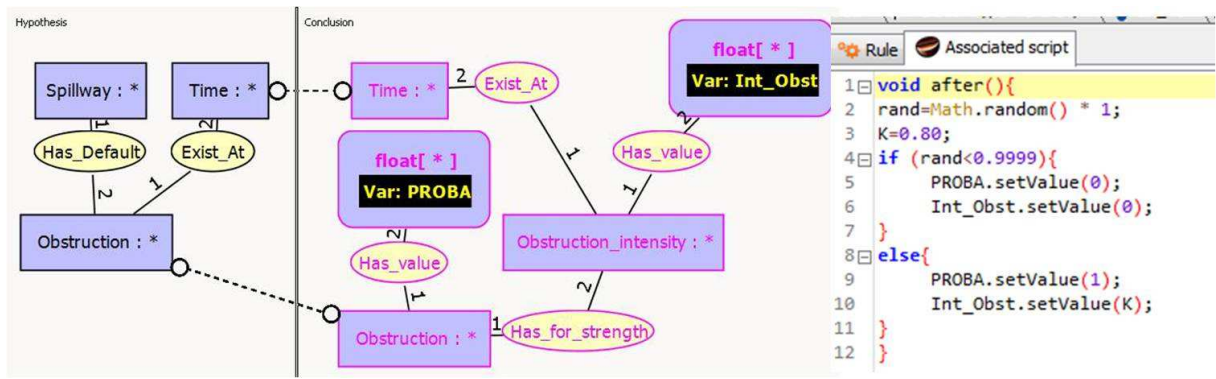
Height (m)	design storm project (m×day <sup>-1</sup> )
27	0.05

555

**Table 1 :** Main properties of the three components of the dam system

556 Many factors such as human errors or natural hazards may cause either immediate or long-term failures. The use  
 557 of scripts in rules allows the capture and representation of random phenomena by introducing probabilistic nodes  
 558 that take into account uncertainty associated with the mechanisms or properties. For instance, in cases of heavy  
 559 rains, vegetation can induce blockage in some pipes. Figure 15 displays the graph rule associated with its script  
 560 allowing the user to assign a probability of obstruction of the spillway and its intensity each day. For instance, in  
 561 the case where there exists a non-null probability of obstruction, we assume that the spillway will be obstructed  
 562 at 80% (denoted by K=0.80 in the script). The probability of obstruction will be lower than 0.01% (denoted by  
 563 “(rand<0.9999)” in the script, Fig. 15) for scenarios (1) and (2) and greater than 99% for scenario (3).

564

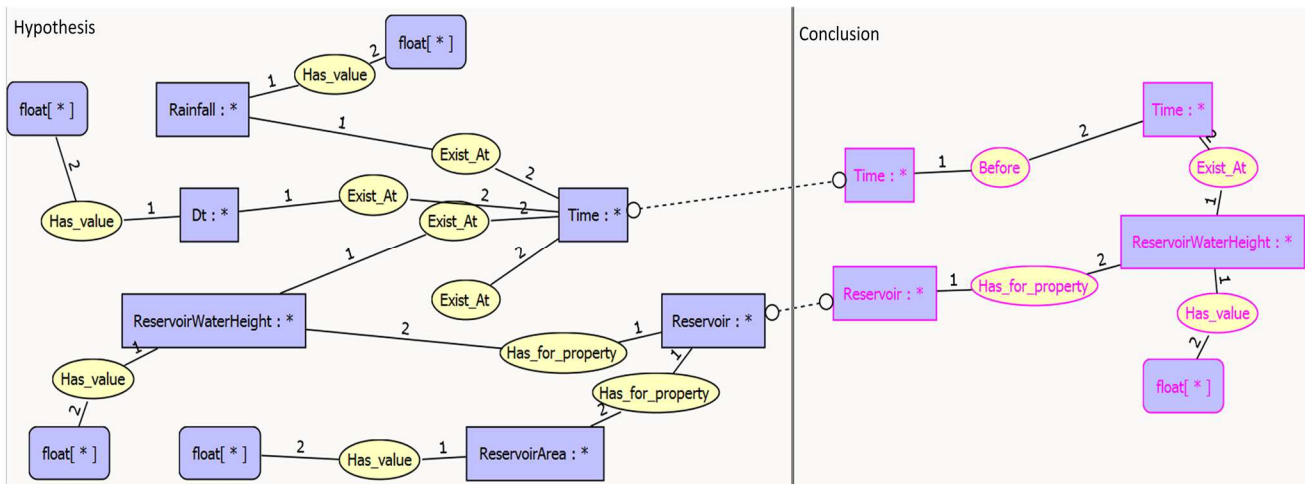


565

566 **Figure 15 :** Rule graph associated with its script allowing the user to assign a probability to the spillway being  
567 obstructed

568 In the **first scenario**, the dam system is confronted with rainfall of  $0.05\text{m}\times\text{day}^{-1}$  over four days. Each day, the  
569 model updates and stores the state of variables over time by using inference rules. Figure 16 displays for  
570 instance, a section of the graph rule allowing the reservoir to update its water level after rainfall over a certain  
571 period. That is if there exists a reservoir  $r$  with its water level  $lw$  at time  $t$  then there exists a new water level  $lw'$   
572 of the reservoir  $r$  at time  $t'$  that updates  $lw$ , after rainfall during  $Dt$ . By using the query-answering mechanism  
573 developed in the framework of CGs (see Section 3), it is possible to query the fact graph database to extract  
574 either all variables or only a set of variables at defined times. For example, Figure 17 displays the request graph  
575 and the answer graph corresponding to the projection of the request graph into the fact graph database containing  
576 the results of scenario 1. The request graph is looking to find the capacity of the spillway to evacuate, the water  
577 level in the reservoir and the horizontal water pressure on the dam body on the second day of rain.

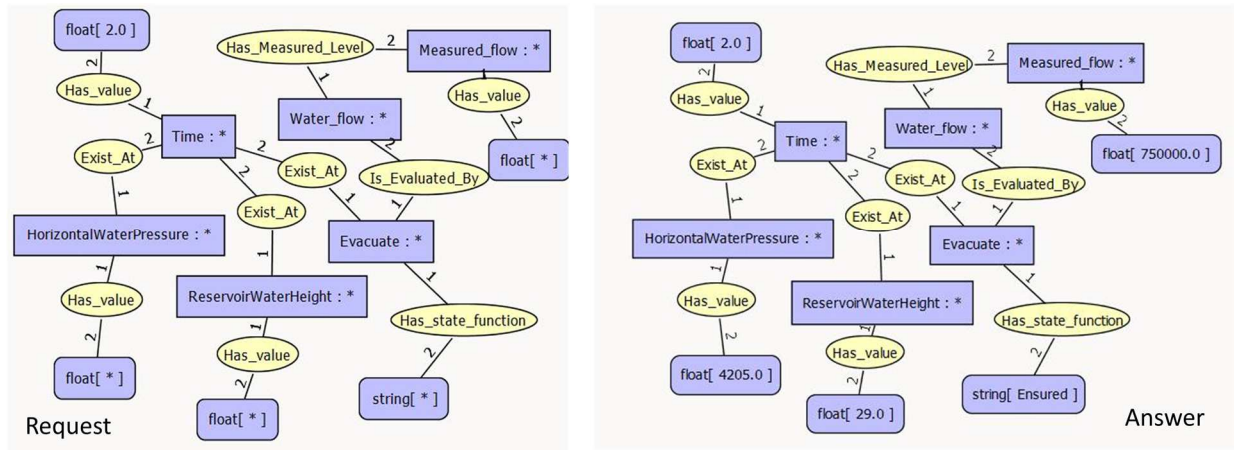
578



579 **Figure 16 :** Section of the rule graph allowing the updating of the water level in reservoir after a *Rainfall* during  
580 a period of  $Dt$

581 The answer graph in Fig. 17 shows that the function of the spillway is ensured. From the answer graph, it is  
582 possible to recover the fact graph in which the request graph has been projected and thus to have an overview of  
583 the dam system over the four days. For instance, table 2 shows a part of the variables extracted from this fact  
584 graph and shows that the spillway correctly evacuates water despite rainfall of  $0.05\text{m}\times\text{day}^{-1}$ .

585



586

587 **Figure 17 :** Request and answer graph regarding horizontal water pressure, sliding stability, reservoir water level  
 588 and inclination

scenario i	Day 0	Day 1	Day 2	Day 3	Day 4
Rainfall ( $m \times day^{-1}$ )	0.05	0.05	0.05	0.05	
Obstruction {0,1}	0	0	0	0	0
Reservoir height water (m)	24	26,5	29	29	29
Crest width (m)	10	10	10	10	10
Dam body self weight ( $kN \times m^{-1}$ )	39600	39600	39600	39600	39600
Dam body height (m)	30	30	30	30	30
Horizontal Water pressure ( $kN \times m^{-1}$ )	2880	3511,25	4205	4205	4205
Spillway function (Ensured/Failed)	ensured	ensured	ensured	ensured	ensured
Function Resist Erosion (Ensured/Failed)	ensured	ensured	ensured	ensured	ensured
Reservoir function (Ensured/Failed)	ensured	ensured	ensured	ensured	ensured

589 **Table 2 :** Simulated results by using inference rules according to a scenario with a constant rainfall for four days

590 In the **second scenario**, the dam system is faced with eight days of rain with an increase of rainfall on the first  
 591 day. Table 3 summarizes a part of the simulated states of variables after using inference rules. The simulation  
 592 shows us that the spillway does not manage to evacuate the water in the reservoir. The level of water (31m) in  
 593 the reservoir runs over the height of dam body (30m) on the third day leading to an overflow. The function of the  
 594 spillway is ensured but it is incapable of evacuating enough water indicating that the spillway has been badly  
 595 designed. This overflow implies an erosion of the crest leading to a 3m decrease of the dam body on the eighth  
 596 day and thus a decrease of horizontal water pressure.

597

598

599

600

601

602

603

scenario ii	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8
Rainfall ( $m \times day^{-1}$ )	0,05	0,07	0,07	0,07	0,07	0,07	0,07	0,07	
Obstruction {0,1}	0	0	0	0	0	0	0	0	0
Reservoir height water (m)	24	26,5	30	31	31	31	31	31	28
Crest width (m)	10	10	10	10	7	4	1	0	0
Dam body selfweight ( $kN \times m^{-1}$ )	39600	39600	39600	39600	38610	37620	36630	36300	32670
Dam body height (m)	30	30	30	30	30	30	30	30	27
Horizontal Water pressure ( $kN \times m^{-1}$ )	2880	3511,25	4500	4805	4805	4805	4805	4805	3920
Spillway function (Ensured/Failed)	ensured	ensured	ensured	ensured	ensured	ensured	ensured	ensured	ensured
Resist Erosion function (Ensured/Failed)	ensured	ensured	ensured	ensured	ensured	ensured	ensured	ensured	failed
Reservoir function (Ensured/Failed)	ensured	ensured	ensured	failed	failed	failed	failed	failed	failed

604

605 **Table 3** : Simulated results by using inference rules according to a scenario with an increase of rainfall from the  
606 first day exceeding the capacity of spillway

607

608 In the **third scenario**, the dam system is faced with eight days of constant rainfall and an obstruction of the  
609 spillway followed by a stop in rainfall and a clearing of the spillway. Table 4 summarizes a part of the simulated  
610 states of variables after using inference rules. The simulation shows us that the water level in the reservoir  
611 increases until an overtopping occurs because the spillway is obstructed leading to an overflow. This overflow  
612 implies an erosion of the crest decreasing its width to 0 but the stopping of the rainfall allowed the spillway to  
613 clear from the 8<sup>th</sup> day, decreasing the water level in the reservoir which implies that the dam system's original  
614 functions are partially restored.

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scenario iii	Day 0	Day 1	Day 2	...	Day 7	Day 8	Day 9	Day 10
Rainfall (m×day <sup>-1</sup> )	0.05	0.05	0.05	...	0.05	0	0	
Obstruction {0,1}	1	1	1	...	1	0	0	0
Obstruction intensity (%)	49%	49%	92%	...	5%	0%	0%	0%
Reservoir height water (m)	24	26,5	29	...	31	31	27	27
Crest width (m)	10	10	10	...	4	1	0	0
Dam body selfweight (kN×m <sup>-1</sup> )	39600	39600	39600	...	37620	36630	36300	36300
Dam body height (m)	30	30	30	...	30	30	30	30
Horizontal Water pressure (kN×m <sup>-1</sup> )	2880	3511,25	4205	...	4805	4805	3645	3645
Spillway function (Ensured/Failed)	Failed	Failed	Failed	...	Failed	Ensured	Ensured	Ensured
Resist Erosion function (Ensured/Failed)	Ensured	Ensured	Ensured	...	Ensured	Ensured	Ensured	Ensured
Reservoir function (Ensured/Failed)	Ensured	Ensured	Ensured	...	Failed	Failed	Ensured	Ensured

624

625 **Table 4** : Simulated results using inference rules according to a scenario with a constant rainfall, an obstructed  
626 spillway for eight days followed by a stopping of rainfall and a cleaning of the spillway

627

### 628 5.3 Forensic engineering

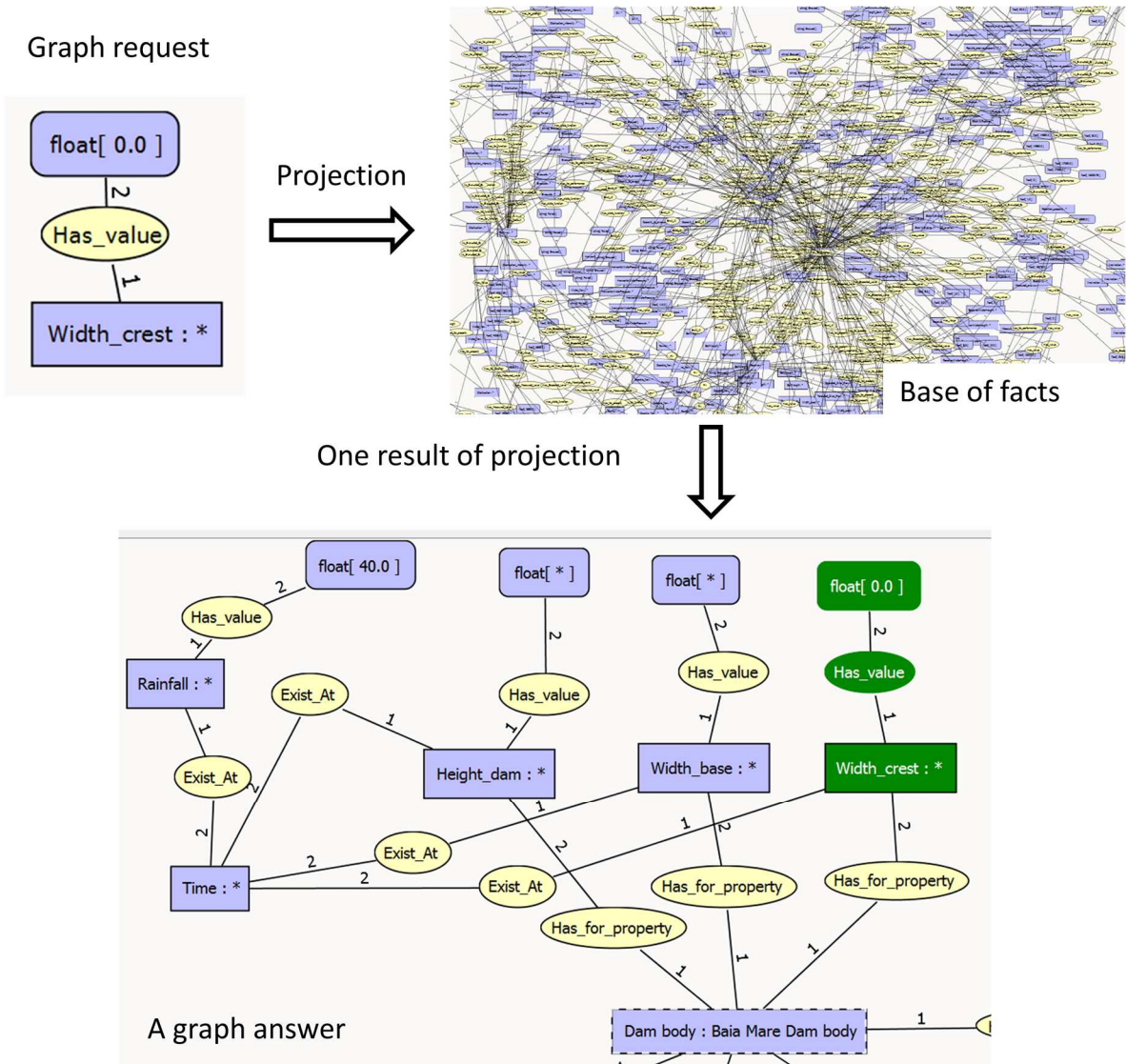
629

630 The aim in this section is to highlight the capacity of our approach to deal with forensic engineering allowing the  
631 definition of the responsibilities (legal issues) and drawing lessons enabling designers and builders or managers  
632 to develop safer alternatives and to improve their practices. The objective is to illustrate the use of the model to  
633 acquire knowledge about past and future failures. Forensic engineering, initially applied in USA in the 50s, has  
634 been widely developed in Anglo-Saxon countries. Nowadays it is used in many fields such as medicine, civil  
635 engineering, road traffic incidents and accidents, planes and fire engineering etc (Noon, n.d.). Forensic  
636 engineering consists in finding possible mechanisms, phenomena, human behaviors, *etc* leading to a failure. In  
637 the biomedical domain, Mujtaba et al., 2018 proposed a conceptual graph-based model to classify forensic  
638 autopsy reports. The model has thus two possible uses: on the one hand to teach lessons and on the other hand to  
639 provide explanations for failures.

640 Assuming that an expert would like to identify situations of a failure similar to a past failure which occurred on a  
641 dam system then, any information about these cases could be valuable for better analyzing a new failure of the  
642 dam and the reasons behind it. The aim is to propose possible explanations based on similar facts. With this aim



643 in mind, the use of request graphs allows users to find similar cases in the available fact graph database. For  
 644 instance, consider that an expert is faced with an embankment dam system that suffered a breach. The expert  
 645 would like to identify situations in which similar failures have occurred previously. The expert may formulate  
 646 his request in the form of a graph (see graph request in Figure 18) and the tool provides a set of fact graphs  
 647 corresponding to the request graph projection in the fact graph database of which the Baia Mare dam is one (see  
 648 a section of graph answer in Fig. 18; on this graph, the elements composing the query were coloured green). For  
 649 instance, the expert knows that there was heavy rainfall (40 mm) when the dam crest was washed away. The  
 650 exploitation of the whole graph will allow experts to know the different state of component functions over time  
 651 that lead to the failure. In fact, the Baia Mare dam collapse resulted from heavy rain and melting snow leading to  
 652 the destruction of dam crest over a length of 25 metres implying the release of 100,000 m<sup>3</sup> of cyanide-  
 653 contaminated liquid into the Lapus stream, tributary of the Somes/Szamos, Tisza/Theiss, and Danube Rivers in  
 654 Romania (Soldán et al., 2001). This use of the tool is similar to a documentary search, in which the tool  
 655 automates the search. This allows the user to benefit from previous concrete examples, allowing them to enrich  
 656 the analysis.



657  
 658 **Figure 18** : Section of one graph answer corresponding to one projection of the graph request in the fact graph  
 659 database.





## 675 6. Discussion and conclusion

676

677 This paper illustrates how the implementation process of the graph-based knowledge model is designed to be  
678 simple to handle and provides a consistent and unified usable practical support tool able to process  
679 heterogeneous knowledge and data. It allows users including scientists, engineers and experts to easily (1)  
680 integrate the interconnected information related to civil engineering systems, (2) perform inferences for  
681 predicting, understanding and learning and (3) derive new knowledge. We are aware that applications remain at  
682 a macro level of detail and the knowledge gained here in these simple applications may seem trivial. A  
683 substantial fact database, documented with hundreds or thousands of cases, will allow users to overcome the  
684 limits of current practices related to expert capacity and memory.

685 The model presented in this paper is still under construction and a first important task will be to build a  
686 sufficiently solid knowledge base covering a wide variety of dam systems (Thesaurus), and to make inferences  
687 (i.e. sufficient rules learned from the fact graph database). The developed model associated with the formalism  
688 of CG is generic enough and versatile enough to deal with various types of dams and failures. The more  
689 complete the database, the more detailed and more valuable the knowledge that can be drawn from it. An  
690 advantage of the model is that it may be updated or enriched in an iterative process without damage to the whole  
691 model. Several solutions can be explored to improve the knowledge base: benchmark with experts, surveys, etc.  
692 In the first stage, the knowledge base will be completed using existing databases already mentioned in the  
693 introduction.

694

695 The current model remains widely deterministic using the first-order logic associated with empirical and  
696 chemical-physical models. The taking into account of uncertainty into account then remains limited in the model  
697 regarding the natural hazards, stakeholder behaviour, *etc.* An improvement of the model could involve  
698 considering probabilistic assessment and modelling. From this perspective, conditional relations would then be  
699 quantified through a probabilistic description by means of the formalism of the probabilistic relational model  
700 where the properties and attributes (*e.g.* the water level in reservoir) of concepts (*e.g.* reservoir) would become  
701 random variables (Baudrit et al., 2019).

702

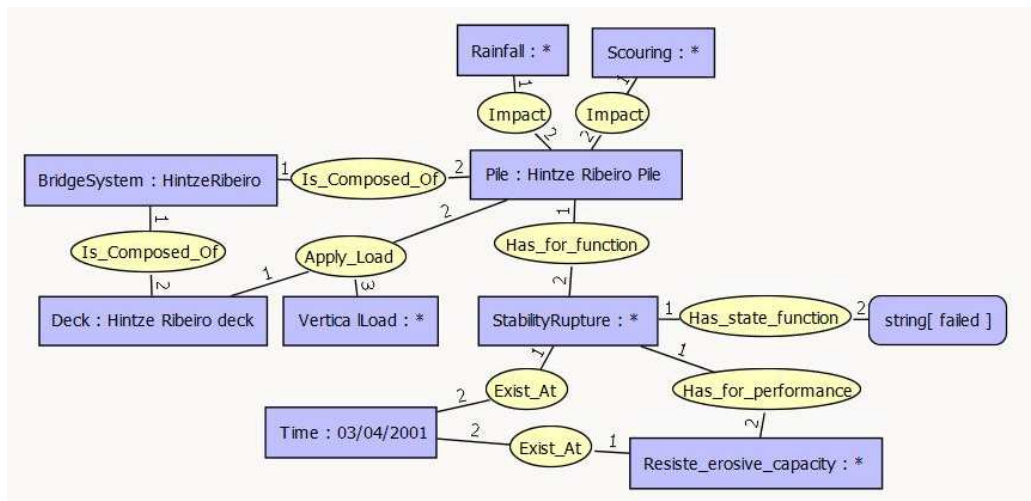
703 This paper presented an original approach that allows scientists, engineers, experts, stakeholders to:

704

- 705 - Represent, implement and store any kind of dam systems in operation or failed in the form of a graph
- 706 - Diagnose and predict the states of each component of a structure in operation
- 707 - Tackle a key issue in forensic engineering that is drawing new knowledge from accumulated data and  
708 facts
- 709 - Enrich and update the model each time new information is available without damage to the whole  
710 structure of model
- 711 - Use easily in practice not only to enter knowledge to build the model but also to understand and to  
712 control the results of the model and how the model computed these results.

713

714 While the present tool is only a seminal version, it appears to be promising for addressing this complex issue,  
 715 and paving the way for a real improvement in forensic engineering, and a wider and more efficient use of failure  
 716 databases. It can be noted that most of the concepts exposed in the section 4.1 are not specific to dams but also  
 717 apply to many other types of constructions (bridges, tunnels, high-rise buildings...), which is an additional aspect  
 718 of the concept. Indeed, by using and enriching vocabulary at the first level and sub levels of the core ontology  
 719 with in section 4.1, it is possible to describe any kind of civil engineering structure along with either their failure  
 720 or their maintenance or both. Consider the example of the collapse of the Hintze Ribeiro bridge over the Douro  
 721 River in Portugal in 2001 (Sousa and Bastos, 2013). The obsolescence of the structure is the major cause of the  
 722 disaster. Erosion of the 116-year old columns and scouring appear to be the main mechanisms responsible for the  
 723 collapse. Scour was aggravated by the extraction of excessive sand for 20 years and the modification of the river  
 724 bed by the construction of upstream and downstream dams. Heavy rains also increased the river's flow. By  
 725 adding for instance Pile and Deck (*resp.* Scouring) as sub concept of Component (*resp.* External Environment)  
 726 in the core ontology of section 4.1, it is possible, to formalize the failure of Hintze Ribeiro bridge that Fig 20  
 727 displays a brief section of what could be the fact graph.



728

729 **Figure 20** : Brief section of the graph fact representing the collapse of the Hintze Ribeiro bridge by using and  
 730 enriching the core ontology of section 4.1

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