Real-time data exploitation supported by model- and event-driven architecture to enhance situation awareness, application to crisis management

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ABSTRACT

An effective *crisis* response requires up-to-date information. The crisis cell must reach for new, external, data sources. However, new data lead to new issues: their volume, veracity, variety or velocity cannot be managed by humans only, especially under high stress and time pressure. This paper proposes (i) a framework to enhance situation awareness while managing the 5Vs of Big Data, (ii) general principles to be followed and (iii) a new architecture implementing the proposed framework. The latter merges event-driven and model-driven architectures. It has been tested on a realistic flood scenario set up by official French services.

KEYWORDS

Situation awareness; EIS for public sector; model-driven architecture; event-driven architecture; complex event processing; crisis management

1. Introduction

Decision support systems have been designed over time to support complex decision-making or complex problem solving. Among them, emergency decision support systems are dedicated to crisis response management. For example, Qiu et al. (2014) propose a method to model cascading crisis events at different levels of abstraction, and Shan and Yan (2017) propose a global framework to handle the supply management as well as, for example, the finance budget management. Emergency decision support systems aim to support multiple agents in unstable environments, for instance on a battlefield or on a crisis cell.

Our goal is to improve the *situation awareness*, as defined by Endsley (1995), of all the stakeholders responding to an emergency, with a new type of information directly deduced from *raw data*, emitted by external data sources. Endsley (1995) defines three levels of situation awareness needed for complex decision-making: (i) the *perception* of data to characterise the crisis situation, (ii) the *comprehension* of the collected data, (iii) the *projection* of the crisis characterisation in the near future.

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We want to prevent them from manually perceiving new data when they are in need of additional information. But, this poses three problems: (i) raw data come with their own flaws and particularities, (ii) the time available to interpret and use these data depends on the crisis (or the battle) itself and (iii) the resulting information is too wide and complex to be communicated without filters or aggregations.

To answer these issues, Section 2 uses a literature review to identify the technical points still to be achieved by the emergency decision support system community. Section 3 presents the methodology followed to bridge these gaps. Section 4 identifies four proposals to be followed by decision support systems wiling to connect to new data sources, and concludes with a proposition for a new decision support system architecture. Then, Section 5 provides some perspectives.

But first, the following introduction defines crisis management, presents issues that could be solved by emergency decision support systems and concludes with the problem addressed in the paper.

1.1. The crisis response management

As defined by Lagadec (1994); Rosenthal and Kouzmin (1997); Devlin (2006), a *crisis* begins when the basic structures, the fundamental values or the fundamental norms of a system are threatened by undesirable outcomes. In 1998, Hoffman, Schuh, and Fenske (1998) were one of the first to use and define the four *crisis management phases*: (i) the *prevention* of future crises' consequences, (ii) the *preparation* to future, unavoidable, crises, (iii) the *response* to every crisis and finally (iv) the *recovery* to reach an acceptable post-crisis situation. The research work presented in this paper focuses on the response phase which is characterised by *time pressure* and *highly uncertain circumstances* as underlined by Rosenthal and Kouzmin (1997).

To face these two issues, a lot of countries have set up their own governmental organisation, like the French crisis organisation illustrated in Figure 1, which follows a circular (Journal Officiel Lois et Décrets (1959)) and a law (Journal Officiel Lois et Décrets (2004)). The French chain of command and control consists of (i) the prefects responsible for one county, as the Loiret (678 722 inhabitants), (ii) the prefects of zone responsible for one of the seven French metropolitan defence zones, gathering one (Paris defence zone) to twenty counties (West defence zone) and (iii) the French president seconded by its prime minister and all their ministries. A crisis cell is set up at each level of the chain of command and control. The upper crisis cell is responsible for the strategy of the crisis response, while the lower crisis cells have to ensure the coordination of all the stakeholders involved in a crisis response. The latter consists of an official manager, agents from network operators, agents from emergency services and civil security agents.

To enable the coordination of the crisis response, as well as the set-up of a suitable strategy, the information describing the crisis situation has to come from the field to the crisis cells while the instructions go form the crisis cells to the stakeholders involved in the crisis response. The number of organisations involved, per the number of threatened territories, suggests that, without proper communication or information management, the collaboration, and thus the decision-making, will not be easy. But,

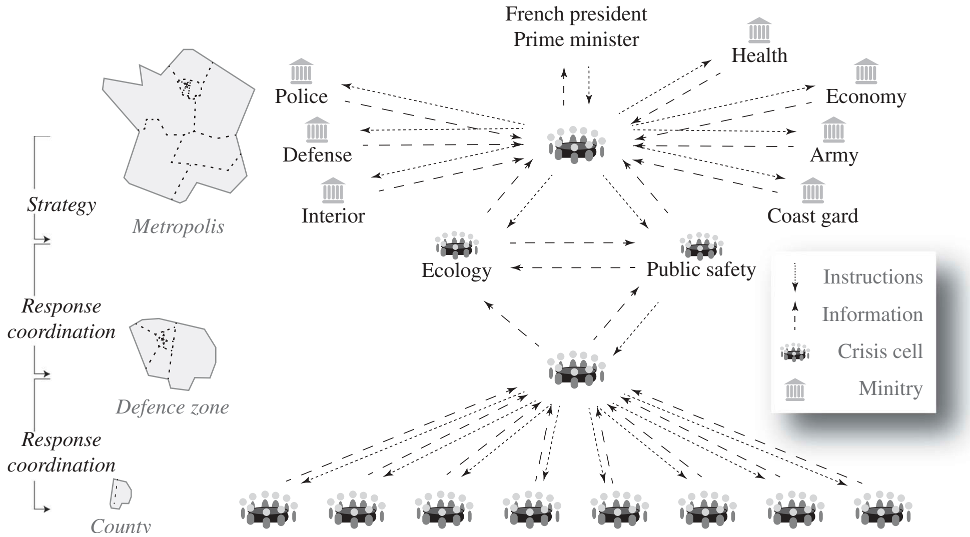

Figure 1. The French governmental organisation during a crisis response (from Ministère de l'égalité des territoires et du logement and Ministère de l'écologie, du développement durable et de l'énergie (2012), and Renou and Dolidon (2015)), illustrated here with a crisis situation on Paris' defence zone.

according to the literature, this is not the only issue faced by decision-makers, during a response phase:

(1) According to Lee et al. (2011), the coordination between *autonomous, heterogeneous* organisations, like our crisis cells, can easily break down because of Klein et al. (2005) *heterogeneous* experiences, information accesses or comprehensions;
(2) According to Shen et al. (2012) or Smith and Hayne (1997), the crisis cells have to face high *information load*, high *stress* and high *time pressure*;
(3) According to Barthe-Delanoë et al. (2014), the innate instability of crises compels the crisis cells to *react* and *adapt* to new events as soon as possible;
(4) According to Klein et al. (2005) and Lee et al. (2011), the organisations involved face *complex* communication channels, consisting of numerous *outdated, incomplete*, or *unavailable* information.

This leads us to consider the following issue, in order to support the decision-makers inside the crisis cells:

-*BI*- Business issue

The crisis cells need support to ensure (i) the consistency of the decisions between the different hierarchical levels, (ii) the coordination of the actions requested from the services involved in the response and (iii) the communication of the right information, at the right level of detail for the right person, at the right time.

1.2. The data available outside the crisis cells

Nowadays, the decision-makers could benefit from the deluge of data and information available outside the crisis cells to tackle most of the issues described above. They could use data sources dedicated to crisis management as the one classified in the *Desinventarlist* (Johansson (2015)) or part of the *Internet of events* as described by Van de Walle, Brugghemans and Comes (2016). Yet, more information does not necessarily mean better situation awareness: this is the so-called *information gap*. Endsley (2012) defines it as the gap between what was expected from the increased volume of actionable information and the actual improvement of the decisions' quality. To avoid this problem, one of the goals of the emergency decision support system, connecting to multiple data sources, must be to improve the situation awareness of its users.

Some authors already worked on information systems and the three levels of situation awareness (perception, comprehension, projection). For example, Blandford and William Wong (2004) propose requirements for systems willing to support the situation awareness of allocators involved in emergency medical dispatch, Kirlik and Strauss (2006) provide organisations with estimation techniques to evaluate interface-mediated situational awareness decomposed in individually measurable components and Webb et al. (2014) propose a model of security situational awareness to help organisations with the confidentiality, integrity and availability of their information resources.

To climb the three levels of situation awareness, a decision support system has to handle several types of information, that have been defined in Table 1. The first column presents the different rows corresponding to a type of information. The first row presents the data layer, the second row the information layer, the third row the knowledge layer and the last row the understanding layer. The last layer could be wisdom, as defined by Ackoff (1989), but, in this paper, we stop at the understanding step. The second column proposes a definition for each layer according to the works of Bierly, Kessler, and Christensen (2000); Bellinger, Castro, and Mills (2004) and Rowley (2007) who work on the – Data – Information – Knowledge – Understanding – pyramid. Sometimes, the understanding layer is mixed up with the wisdom layer. The definitions also refer to the works of Endsley (2012) on designing situation awareness. The last column refers to the clear set of definitions proposed by Ackoff (1989).

An emergency decision support system, willing to receive new data or data streams from external data sources, will have to tackle five issues linked to the 5Vs of Big Data, as

Table 1. The pyramid from data to information, from information to knowledge and/or from information to understanding.

	Definition of the paper	Ackoff (1989) definition
Data (D)	De-contextualised information or bit of information	Properties
Information (I)	Data contextualised to support the users' goals (Endsley 2012; Rowley 2007)	Descriptions (what?, where?, how many?, ...)
Knowledge (K)	Information combined for decision support (Rowley 2007; Bierly, Kessler, and Christensen 2000)	Instructions (how-to?)
Understanding (U)	Information extrapolated to predict near-futures (Bellinger, Castro, and Mills 2004; Rowley 2007)	Explanations (why?)

Table 2. Definitions for the 5Vs of Big Data along with the issues to be dealt with in this paper.

	Definition of the paper	Linked issue
Volume	Amount of data generated (Xu and Duan 2019; Ghasemaghaei 2019), to be processed (Krishnan (2013); Kaisler et al. 2013) that is proportional to the amount of data sources	How to process only the data and information that will be useful for the decision-making?
Velocity	Speed needed to process data before their *expiration date* in a rapidly changing environment (Kalyvas and Albertson 2014; Fan and Bifet 2013; Marr 2015b) due to real time (Ghasemaghaei 2019) social interactions, sensor monitors or business activities (Xu and Duan (2019))	How to process the data and information in real-time, or near-real-time?
Variety	Diversity of data and formats (Ohlhorst 2012; Demchenko et al. 2013; Marr 2015b), as well as the diversity of data sources (Ghasemaghaei 2019), use to ease the capture of useful patterns (Xu and Duan 2019)	How to manage the diversity of data inside the system?
Veracity	Accuracy, trustworthiness of the data to be processed (Marr 2015b; Xu and Duan 2019) as well as the quality, accuracy and trustworthiness of generated information (Yang et al. 2017), completed by the credibility and the objectivity (Lukoianova and Rubin2014)	How to ensure the credibility, the truthfulness and the objectivity?
Value	Mix of quality (Lukoianova and Rubin 2014), and usefulness (Kaisler et al. 2013); ability to turn the data into value (Marr 2015b)	How to process only the useful data to obtain information useful for the decision-makers?

described in Marr (2015a) and later in Yang et al. (2017): the Volume, the Value, the Veracity, the Velocity and the Variety. All 5Vs are described in Table 2. The first column presents the different rows corresponding to each V of Big Data. The second column proposes a definition for each V of Big Data according to (i) the work of Krishnan (2013) and Ghasemaghaei (2019) on the first 3Vs of Big Data (Volume, Variety and Velocity), (ii) the work of Lukoianova and Rubin (2014) that considers, in addition, the Veracity and (iii) the works of Demchenko et al. (2013); Fan and Bifet (2013); Kaisler et al. (2013); Marr (2015b); Xu and Duan (2019) that speak of the 5Vs of Big Data. Sometimes some other Vs are proposed as the Variability chosen by Fan and Bifet (2013) or the Complexity chosen by Kaisler et al. (2013).

The 5Vs' issues, enlightened by the business issue *BI* of this introduction, lead us to the main problem of this paper:

-P- Problem statement

What type of architecture should be set up to enable a decision support system to continuously climb the 3 levels of situation awareness, display activable information on a common operational picture inside each crisis cell, while managing the the volume, variety, velocity and veracity of the data processed to obtain new information in order to improve the value of the resulting situation awareness shared inside the crisis cells?

1.3. The proposed framework

To solve the problem $-P-$, we propose a dedicated framework shown in Figure 2. Each row corresponds to one level of situation awareness: the perception, the comprehension and the understanding. Each level relies on the levels below. The perception aims to generate information from data. The comprehension aims to generate knowledge from information and the understanding aims to generate understanding from information

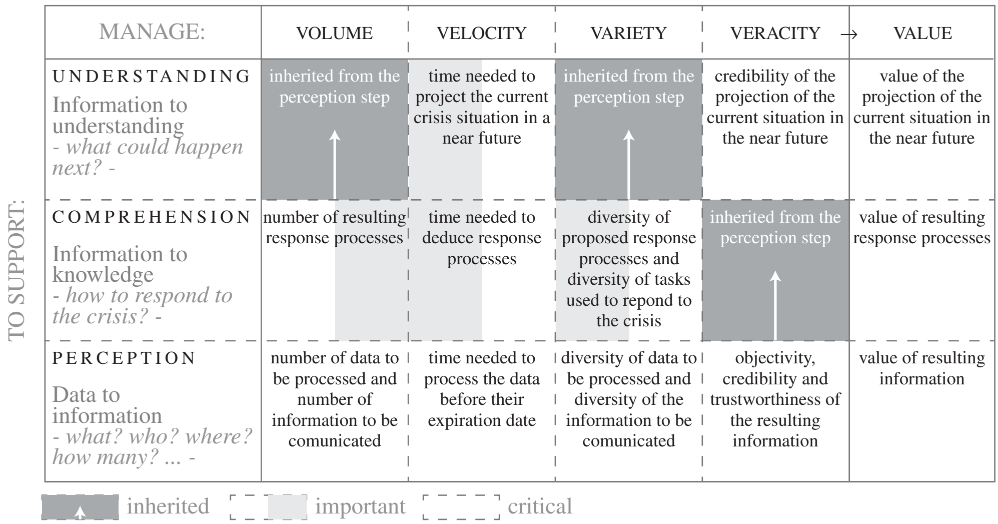

Figure 2. The proposed framework to support the design of a new emergency decision support system, able to connect to diverse, external, data sources, in order to improve their users' situation awareness.

and knowledge. For example, in a crisis cell, the perception step could result in a common operational picture, the comprehension step in a suitable process for the organisations involved to respond the current crisis situation, and the understanding step in a projection in the near future of the current common operational picture.

Every emergency decision support system willing to enhance the situation awareness of their users will have to achieve these three steps. To automate this process, it can connect to diverse data sources or information sources, but then it will have to manage the volume, velocity and veracity of both the data available and the information generated to feed the comprehension and understanding steps. If it succeeds, it can then aim to improve the value of the data it processes and the information it generates. The columns represent each one of the 5Vs of Big Data to be managed along with their importance for each level of situation awareness (row): important or critical. For example, the velocity has to be managed at the perception level to avoid missing the processing of critical data. But then the information can be communicated to the decision-makers in the minutes that follow (which is far from the multiple data to be processed in milliseconds). In some case, upstream management of 1V can be automatically reflected downstream. For example, the volume of information generated at the perception level directly impacts the volume of information to be projected in the near future at the understanding level.

A literature review performed on Web of Science with the query (('situation awareness' OR 'situational awareness') AND ('Big Data')) returned 16 computer science articles and reviews. Among them seven were proposing a general approach, or an architecture, to ascend the three levels of situation awareness, but none of them was tackling more than the volume of Big Data. This concerns Avvenuti et al. (2018), who analyse social media data; Wu et al. (2018), who propose a security situational awareness; Nguyen et al. (2018), who detect malware intrusions automatically; Hingant et al. (2018), who propose to combine cyber and physical data; Ma and Zhang (2017), who propose a data-driven knowledge management system; and He et al. (2016), who conduct situation awareness with a model-free data-driven procedure. At last, Ning et al. 2016 propose an Internet hierarchy to achieve thinking computing. They propose a lot of definitions but do not address the issues related to the 5Vs of Big Data. As a contribution, the goal pursued by the proposed framework is to offer a repository for all the emergency decision support systems willing to support complex decision-making, in a hurry, by connecting to a wide range of data sources in order to enhance the situation awareness of their users.

2. Literature review: existing techniques to enhance situation awareness while managing one of the 5Vs' issues

We choose to focus on the critical Vs to be managed at each level of situation awareness: all the research works presented below enable to manage at least one of them. A resume of this literature review is available at the end of the section.

2.1. Existing solutions to deal with the volume

Only a few techniques reduce the amount of data and information to be processed, according to their predicted usefulness. These are two examples:

- Rosman et al. (2014) propose to use corsets, instead of approximation algorithms or video summarisation techniques to deal with the data volume, due to financial times series, GPS data analysis or video streams. As defined in Har-Peled and Kushal (2007), a corset is an optimal small portion of data that is a fundamental combinatorial property of a clustering problem;
- Chen and Zhang (2014) propose to deal with the volume through the choice of algorithm or software architecture. They use cloud computing, an algorithm with good scalability properties and distributed computing to aggregate multiple workloads into a large cluster of processor. To efficiently process a large volume of data, they refer to disciplines as statistics, data mining, machine learning, neural networks, social network analysis, signal processing, pattern recognition, optimisation methods and visualisation approaches.

2.2. Existing solutions to improve the value

The value of all the information handled by an emergency decision support system depends on their potential usefulness for the decision-makers in each level of situation awareness. Here, the higher the level of situation awareness, the more valuable the information. To enhance this value while ascending the three levels of situation awareness, several techniques can be used:

- Yin et al. (2015) propose to extract 'situational awareness' information from social media during disasters. They use five different natural language processing and data mining techniques: tweet filtering, classification, clustering, geotagging and burst detection which allows to detect a 'burst of activity' on a given topic (Kleinberg 2003).

- Bénaben et al. (2017) propose to follow the model-driven architecture principles to deduce a response process suiting the goal of the partners of an ongoing crisis collaboration, through the use of a dedicated meta-model presented in Lauras et al. 2015. Their work is implemented on the R-IOSuite tool suite developed by Salatgé et al. (2019). As defined by Chungoora et al. (2013), model-driven architectures use three points of view of the same system: the computation independent model, the platform independent model and the platform specific model. The link between one model and another is ensured by model transformation rules, used, for example, in Bénaben et al. (2017) to deduce a collaborative process and therefore reach the comprehension level.
- Marie et al. (2013) propose a meta-model dedicated to represent the quality (value) of contextual information;
- Brannon et al. (2009) propose to enhance the situation awareness of decision-makers through the use of a system that combines the three available learning techniques. As defined in Russell and Norvig (2010)[1]: there is the supervised learning based on inputs and expected outputs given by a component or an expert, the reinforcement learning when the system receives evaluations during its operation and the unsupervised learning when no hints are available about the correctness of the outputs. Brannon et al. (2009) implement their work on the CARTMAP system able to switch its learning mode to enhance vehicle tracking on a map given seismic and acoustic sensor data.
- Itria et al. (2017) propose to rapidly collect, filter and aggregate heterogeneous data to support decisions. They use a complex event processing engine to correlate data and generate complex event describing an ongoing critical situation. As defined by Etzion, Niblett, and Luckham (2011), complex event processing engines use event processing agents to apply complex event processing rules in order to detect events, filter events and generate new events, therefore called complex events. Complex event processing is referred to as stateless: the process of one event does not influence the way subsequent events are processed. As defined by; Luckham and Schulte (2011), events are computerised objects that represent, encode or record real events. A real event is anything that happens, is happening or will happen. Barthe-Delanoë et al. (2018, 2014, 2012) also propose to use complex event processing, coupled with a mediation information system to model crisis, thanks to a dedicated meta-model proposed originally by Bénaben et al. (2008). Here, the complex event processing is used to follow an ongoing crisis situation and detect major evolutions.
- Comes et al. (2011) propose new reasoning techniques to support decision-making under uncertainty, through the enhancement of the understanding level of situation awareness. This approach is complementary to principles that support decision-making under ignorance: deterministic, probabilistic, fuzzy, etc. Comes et al. (2011) propose to generate different possible scenarios of the near future. To structure their information they use directed analytic graphs, like casual maps, to support multi-criteria decision-making.

2.3. *Existing solutions to enhance the veracity*

The veracity of all the data and information handled by an emergency decision support system can increase, thanks to different techniques:

- Puthal et al. (2017) propose to verify, in real-time, the authenticity and integrity of data received in streams to secure exchanges with external data sources. They propose to use a shared key that is updated automatically at both ends while limiting communication overheads.
- Itria et al. (2017) propose to use anomaly detection techniques to assess the result of their complex event processing that combine tweets and sensor data to enhance the perception level of situation awareness during a crisis situation. As defined by Chandola, Banerjee, and Kumar (2009), anomaly detection enables a system to find patterns in data that do not conform to expected behaviours.
- Lim et al. (2016) propose to complement the security solutions that exist along with publish/subscribe protocols. They propose to set up an authorisation mechanism that checks the intended use of the data before granting access. As underlined in Uzunov (2016), Publish/Subscribe security policies already propose to manage message encryption, secure routing, identification, digital signature, quotas or process replication.
- Brannon et al. (2009) propose to augment their CARTMAP system with a situation assessment module. The module takes in input several types of data as the wind speed or a vehicle speed and assesses the current level of threat, thanks to a weighted rule combining all the inputs.
- Comes et al. (2011) propose to assess their different scenarios of the near future dedicated to enhance the understanding level of situation awareness. They propose to use the multi-attribute decision-making technique that suits both decision-making under certainty, with the multi-attribute value theory, and decision-making under risks, with the multi-attribute utility theory.

2.4. *Existing solutions to follow the velocity imposed by the crisis*

Several techniques fit *real-time* constraints:

- Pongpaichet et al. (2013) propose to recognise evolving situations from data streams in real time. Their framework, called EVENTSHOP, enables to analyse tweets, referring to a given hashtag, and map them. This is done, on request, every few hours. As underlined in Atefeh and Khreich (2015), several techniques can be used to detect events from microblogging data streams (naive bayes classifier, online clustering, support vector machine classifier, hierarchical divisive clustering, discrete wavelet analysis, continuous wavelet analysis, gradient boosted decision trees, factor graph model, statistical modelling of crowds, recursive query construction, generative language modelling, temporal query expansion technique or event modelling). For instance, Schulz, Ristoski, and Paulheim (2013) use a supervised classifier, trained with incident types, to detect small incidents in streams of tweets;

- Barthe-Delanoë et al. (2018, 2014, 2012) propose to bridge the gap between systems and 'things that happens in the real world'. They propose to use an event-driven architecture that enables to retrieve both real-time and historical data. Technically, they implement a complex event processing engine. As underlined in Theorin et al. (2017), an event-driven architecture is extremely loosely coupled and highly distributed. Additionally Theorin et al. (2017) underline that complex event processing engines process data efficiently and immediately recognise interesting situations when they occur. As defined by Cugola and Margara (2012), complex event processing extends the publish/subscribe approach by considering complex event patterns that involve the occurrence of multiple, related events. Complex event processing engines themselves can be implemented following a centralised, hierarchical, acyclic or peer-to-peer architecture.

2.5. Existing solutions to tackle the variety problem

Finally, several techniques are used to deal with the variety issue: the diversity of data inside the system:

- Pongpaichet et al. (2013) propose to use the semantic Web, geographical information system and spatio-temporal modelling to manage the variety of data streams, which are, according to them, often associated with a time and metadata. For instance, Boulos et al. (2011) stress the great enthusiasm for using volunteered geographic information, participatory sensing, bicycle-mounted sensing or indoor/outdoor surveillance sensing, combined with semantic web technology, to feed future crisis cells with activable, located, information.
- Barthe-Delanoë et al. (2018, 2014, 2012) propose to receive events sent by heterogeneous sources, thanks to the OASIS Web services notification standard. As defined by Niblett and Graham (2005), these specifications define the protocol through which Web services can disseminate events. They consist of: (i) the Web services base notification specification described by Graham, Hull, and Murray (2006), (ii) the Web services topics specification described by Vambenepe, Graham, and Niblett (2006) and (iii) the Web services brokered specification described by Chappell and Liu (2006). For instance, in crisis management, Vescoukis, Doulamis, and Karagiorgou (2012) recommend the open geospatial consortium to implement specific Web services to exchange large amount of heterogeneous geospatial content.
- Jeong and Ghani (2014) propose to semantically deal with the variety issue through ontology-based approaches, ontology evolution approaches or semantic filtering and reasoning approaches.

2.6. Gaps still to be bridged

As a result of the literature review presented above, Figure 3 sums up the effects of each solution on the five Vs of Big Data. The first column lists all the solutions identified in the literature review. Each solution is evaluated given its ability to manage the volume (second column), the variety (third column), the velocity (fourth column), the veracity

Solutions	Volume	Velocity	Variety	Veracity →	Value	Percep.	Compr.	Unders.
Corsets	V					X		
Distributed and cloud computing	V					X	X	X
Statistics, data mining, classification, clustering, machine learning, burst detection, neural networks, networks analysis, signal processing, pattern recognition, optimization, vizualisation approaches	V				V	X		X
Model driven architecture			V		V	X	X	X
Event driven architecture, complex event processing, stream processing	V	V			V	X		
Multi-attribute value					V			X
Common shared key				V		X		
Anomaly detection	V	V		V		X		
Access control, publish/ subscribe security policies				V		X		
Confidence level, multi-attribute value theory				V		X		X
Metadata, Semantic web			V			X		
Web service notification standard	V	V	V			X		

V V tackled down   X level of situation awareness enhanced

Figure 3. Existing techniques that can enhance one of the situation awareness needed inside the crisis cells while managing one of the 5Vs of Big Data.

(fifth column) and the value (sixth column). Each solution is also given along with its role on climbing the three levels of situation awareness: the perception (seventh column: data to information), the comprehension (eighth column: information to knowledge) and the understanding (ninth column: information to understanding).

It should be explored by further research works, but there seems to be no solution that manages the 5Vs of Big Data while enhancing the three levels of situation awareness. Hopefully, some solutions given in the literature review are compatible with each other.

Figure 4 completes Figure 3 with our proposition. We propose to combine complex event processing, Web service notification, Publish/Subscribe, model-driven architecture and machine learning techniques in order to manage the 5Vs of Big Data. We aim to enhance the three levels of situation awareness inside crisis cells.

Solutions	Volume	Velocity	Variety	Veracity →	Value	Percep.	Compr.	Unders.
Complex event processing AND web service notifications AND publish/subscribe AND model driven architecture AND machine learning	V	V	V	V	V	X	X	X

V V tackled down   X level of situation awareness enhanced

Figure 4. Proposition following the literature review.

3. Methodology: from the literature review to a new architecture design

Our work started with the interviews of several practitioners experienced in crisis response management. We aimed to (i) recover the difficulties faced by managers during crises or drills, and (ii) extract business rules from their doctrines. The specifications, which followed the interviews, have been written by Renou and Dolidon (2015) and are consistent with the issues introduced in the introduction. The interviews, mixed with the theory introduced in Section 2, led us to validate three assumptions:

(1) If the information is shared effectively (at the right moment, to the right person, at the right level of abstraction), connecting to multiple data sources will enhance the situation awareness inside the crisis cells;
(2) The use of interactive common operational pictures will effectively communicate information from a decision support system to the decision-makers inside the crisis cells;
(3) The ascent of the three levels of situation awareness, supported by a decision support system, will improve the decision process inside the crisis cells.

First, we can observe that these needs, collected on the field, are consistent with the problem statement given in the introduction. Therefore, the proposed framework can be applied to look for suitable emergency decision support system specifications. In addition, we already found a suiting set of technical solution that fits the requirements of the prosed framework (cf. Figure 11). Thus, the next section poses the foundation for an emergency decision support system designed to answer the problem $-P-$ through (i) the design and (ii) the implementation of an architecture compliant with:

- *The model-driven architecture* proposed by Bézivin and Olivier (2001) to ensure the completeness, consistency and relevance of all the information processed in a system, while accelerating the information's updating process, through the instantiation of a meta-model;
- *An event-driven architecture and a complex event processing engine* proposed by Luckham and Schulte (2011) to enable a system to receive, filter and aggregate computerised events describing real events, thanks to a complex event processing engine as implemented by Itria et al. (2017) or Barthe-Delanoë et al. (2018);
- *The Web service notification standard and the publish subscribe paradigm* proposed by Graham, Hull, and Murray (2006) to complete the event-driven architecture principle with publish/subscribe specifications, in order to receive events from both known and unknown sources, thanks to the use of common topics.
- *Machine learning techniques* to anticipate the state, in the near future, of some element of the crisis situation as the water level of a river, the rainfall over a region, etc.
- These four proposals are the basis for a new type of decision support system able to meet the requirements induced by the problem $-P-$. They also manage to meet the expectations of Slam et al. (2015) towards future

emergency decision support systems. Their expectations are listed below, supplemented by our proposals in parentheses:

- Represent a current crisis situation (perception), through an effective knowledge representation scheme (meta-modelling) and being able to reason upon it (comprehension);
- Adapt to the evolutions of the current crisis and support the decision-making in real time (continuous analysis of event streams);
- Adapt to the different characteristics of disasters to come (genericity of the meta-model).

4. The proposed architecture to support crisis cells

This section introduces one way to follow the framework, and therefore answer the problem $-P-$, assuming that the three assumptions from Section 3 are true. Figure 5 presents our proposal given the proposed framework (cf. Figure 2). The technical ascent of the three levels of situation awareness is presented below:

- To enhance the perception level of situation awareness inside the crisis cells, we propose to use a complex event processing engine supported by an event-driven architecture. It manages, in streams (*velocity*), hundreds of computerised events (*volume*) available to the crisis cells (hydrological events, social media events, meteorological alerts, etc.). In addition, the Web service notification standard manages the *variety* of inputs, and the publish/subscribe security policies ensure the origin of the events (*veracity*). They are all represented at the bottom of Figure 5.
- To enhance the comprehension level of situation awareness inside the crisis cells, we propose to follow the work of Bénaben et al. (2017) that uses a model of a current crisis situation to deduce a suited response process in real time (*velocity*). This is represented in the middle of Figure 5.
- To enhance the understanding level of situation awareness inside the crisis cells, we propose to use forecasts given by machine learning tools or existing forecast services to feed our complex event processing rules in addition of events describing the ongoing crisis situation. The output information is used to update a *projected* picture of the crisis situation in the near future. Besides, if a response process is running, its expected outcomes are added to the projected model. These are represented at the top of Figure 5.
- To communicate the set of information describing the ongoing crisis or its projection in the near future, we propose to use a common operational picture. One common operational picture is made available for each crisis cell. It is adapted to the need of each level of command and control (*volume* & *value* & *variety*) (cf. Figure 1) and the users can manually update (*veracity*) (i) an information concerning the crisis situation, (ii) a part of the response process proposed by the decision support system.

Figure 6 details the proposed architecture that implements this proposal. We aim to update common operational pictures, suited to each level of the French chain of command and control: they are represented at the top, in dark grey. To update them in real time, thanks to streams of raw events, the architecture consists of four modules (white boxes) and connects to an existing decision support system called R-IOSuite represented

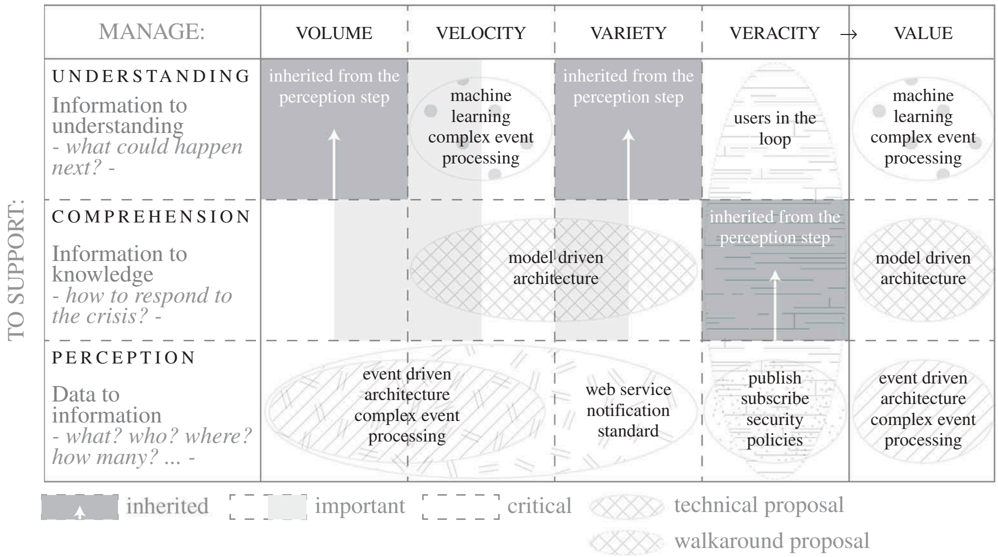

Figure 5. Our proposal coverage of the proposed framework.

within the light grey area at the right of Figure 6. The proposed modules are: the Learning engine, the Interpretation engine, the Visualisation engine and the Simulation engine. All these modules process data, information, knowledge or understanding (cf. Table 1) stored in the system (grey boxes). The arrows represent their circulation inside the proposed architecture along with a description of their content.

4.1. How the proposed emergency decision support system reaches the perception level of situation awareness?

The Interpretation engine, the module at the bottom right of Figure 6, analyses event streams to update the situation model: the representation of the current crisis situation stored in the system and represented at the right of Figure 6. It is structured by the Meta-model presented in Figure 7 that inherits from the work of Bénaben et al. (2017). It is made of a CORE dedicated to describe collaborations, in grey on Figure 7, and a LAYER inheriting from the CORE, represented by a striped background. The latter is dedicated to describe crisis collaboration. A crisis collaboration is made of *Partners*, i.e. stakeholders of the crisis response, that aims to prevent *Risks* and deal with *Incidents* threatening vulnerable assets as a *Network*, a hospital (*Sensitive building*), a SEVESO site (*Hazardous building*) or a *Dyke*, in case of a flood.

An example of a situation model, respecting the proposed meta-model, is given in Figure 8. It describes a crisis situation that could follow a major flood of the French River Loire. It focuses on Orléans, a French city located on a map at the top right of Figure 8. According to this model, a risk of failure threatens the main dyke of Orléans and a risk of flooding threatens the nearby hospital and the main train station. The situation model consists of instances of the meta-model's concepts represented in grey. The links between the model and its meta-model are represented by dotted links.

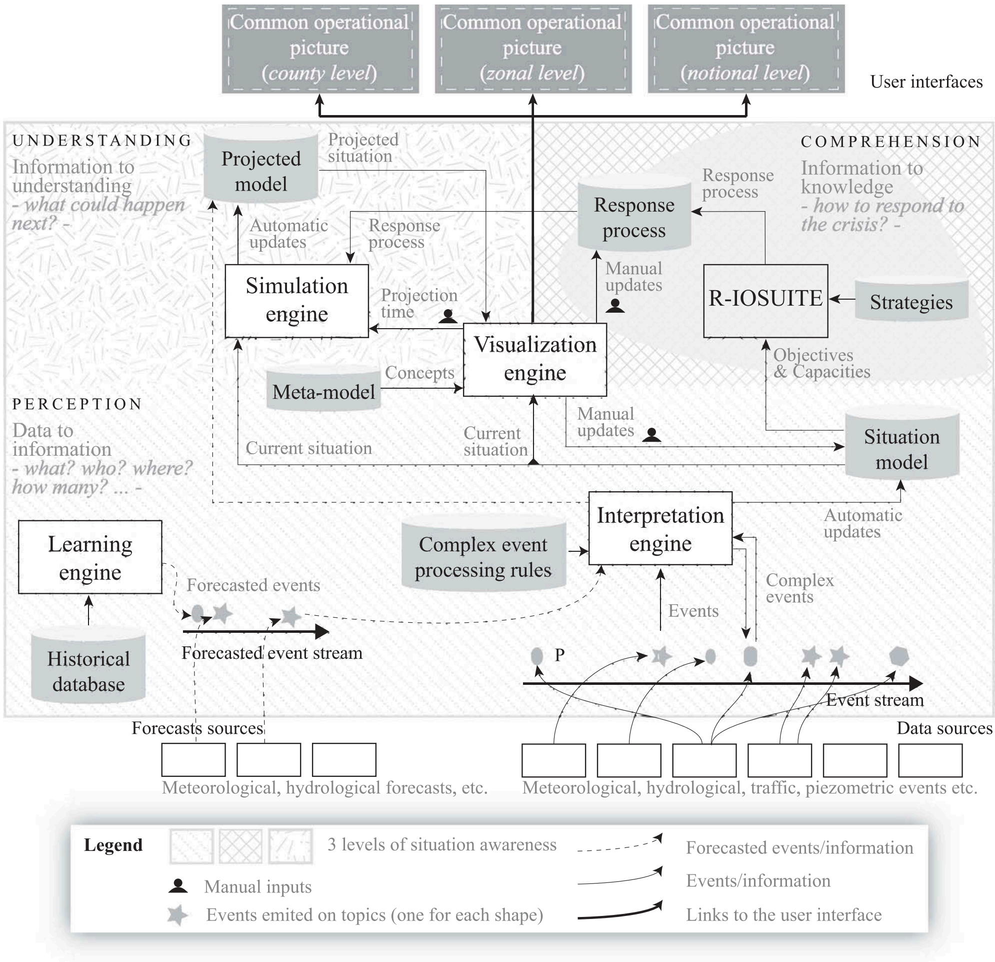

Figure 6. The architecture proposed for all decision support systems willing to enhance the situation awareness of their users by connecting to multiple, heterogeneous data sources while managing the 5Vs of Big Data.

To keep the situation model updated regarding the ongoing crisis situation, the Interpretation engine uses a complex event processing engine. It generates complex events by analysing streams of computerised events through a moving time-window as described by Luckham and Schulte (2011). Because it can subscribe to his own complex events, one event can be processed multiple times. The analysis is made by event processing agents that apply complex event processing rules represented in the middle of Figure 6.

A complex event processing rule can filter, aggregate and generate events. Our main contribution enables the complex event processing engine to issue specific complex events that directly ask for the update of the Situation model while being able to query it. An example inspired from Bénaben et al. (2015) is given below. For instance, an event describing a water level higher than the safety level of a nearby dyke triggers a Danger of flooding for the neighbourhood. Then, thanks to the rule (1), the complex event

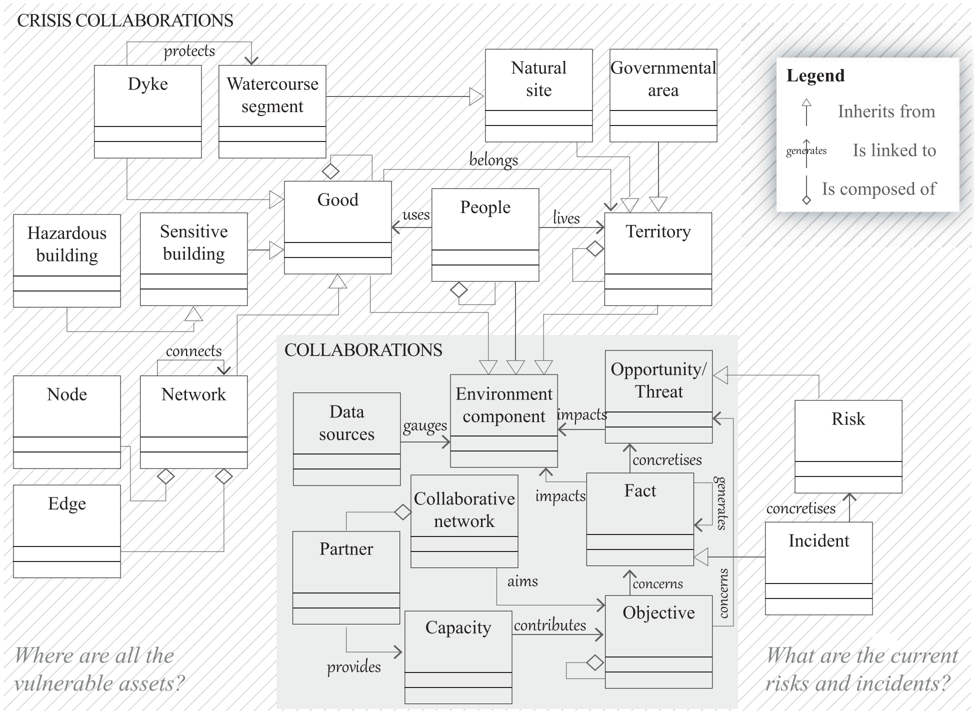

Figure 7. The proposed meta-model inherited from the R-IOSuite meta-model (Bénaben et al. 2017).

concerning the Danger of flooding triggers a Risk of victims for each occupied building and a Risk of panic for each school in the danger zone.

$$\begin{array}{l} \forall \text{ instance } x \text{ of Vulnerable Asset} \in \text{ Situation model,} \\ \text{And } \forall \text{ instance } y \text{ of Danger} \in \text{Situation model,} \\ \text{If } y \text{ impacts } x\text{, then, add on the Situation model an instance } z \text{ of Risk that :} \\ -\text{impacts } x \end{array} \quad (1)$$

To receive and emit events the architecture relies on the Web service notification standard and the publish/subscribe paradigm.

4.2. *How R-IOSuite deduces a suited response process thus climbing the comprehension level of situation awareness?*

The R-IOSuite decision support system, at the top right of Figure 6, uses the Situation model to deduce a response process suited to the crisis cells, as described in Bénaben et al. (2017). Because they use the same meta-model, interoperability issues are avoided. R-IOSuite is developed by Salatgé et al. (2019) and available at https://R-IOSuite.com/display/RIOSUITE/BinariesR-IOSuite.com.

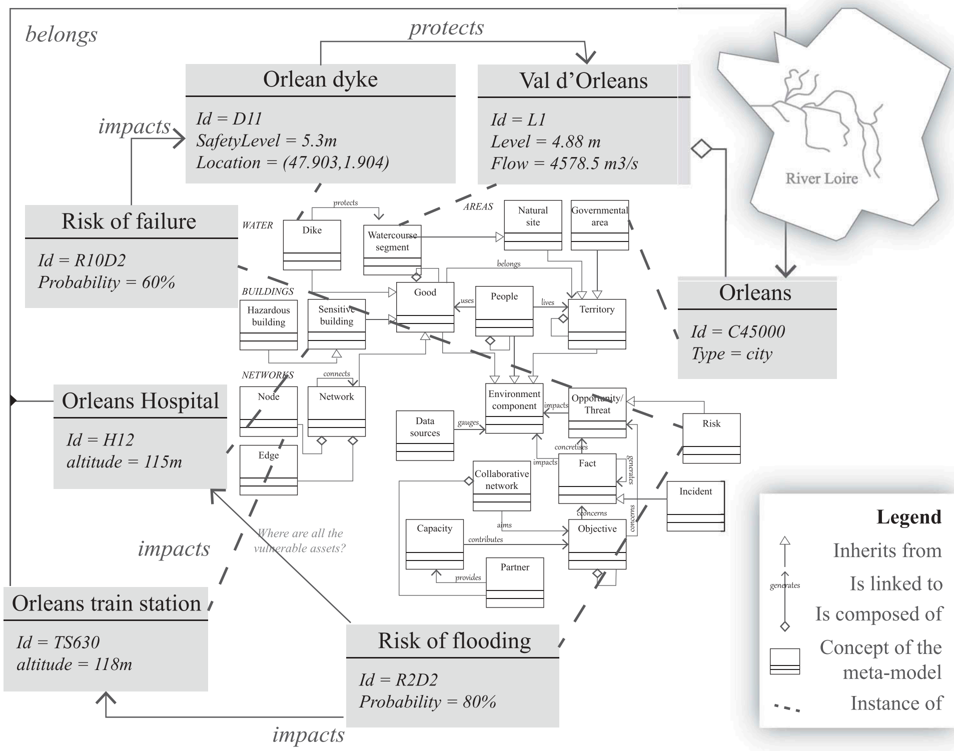

Figure 8. Extract of a situation model describing the consequences of a major River Loire flooding.

4.3. How the proposed emergency decision support system anticipates the near future to reach the understanding level of situation awareness?

To reach the understanding level of situation awareness, the proposed emergency decision support system uses two modules: the proposed Learning engine, in charge of machine learning on past crisis and the proposed Simulation engine in charge of the update of the projected situation model.

4.3.1. How to forecast the state of some critical elements, during a crisis situation?

The Learning engine the module at the bottom left of Figure 6, applies machine learning techniques on historical data, in order to forecast the predictable evolution of some of the components composing the crisis theatre. The French weather forecast service, MeteoFrance, counts indeed on machine learning to revolutionise their current forecasting models. The results of the forecasting process, called *Profiles*, represent the evolution of a *Key variable* in time. One example of a Profile is given in Figure 9. This one is inspired by the work of the French flood forecast services. At the right of the graph, the black line represents the past. At the left, from bottom to top, the first curve represents forecasted water levels that have 90% chance of being reached. The second curve, 50% chance, and the last curve 10% chance.

At present, in case of a flood, for example, the proposed emergency decision support system uses only streams of forecasts received from official French services, in charge of forecasting the water level and flow level of all the French Rivers. An overview of these data, made publicly available before the forecasting process, is available at https://www.vigicrues.gouv.fr/Vigicrue.gouv.fr.

4.3.2. How to use forecasts and the running response process to project the situation model in the near future?

The simulation engine, the module at the top left of Figure 6, uses Profiles (cf. Figure 9), to obtain one scenario of the near-future, called the *Projected model*, represented at the top left of Figure 6.

For each projection time, t_p, wanted by the users, the Simulation engine makes a copy of the current Situation model and calls it the Projected model of t_p. For each Projected model, the Simulation engine applies the expected consequences of the Response Process deduced and orchestrated by R-IOSuite. For example, in the event of a major flood, an order to set up accommodations and then evacuate could be issued by the officials. These two tasks come with an estimation of duration, 24 h to set up accommodations and 48 h to evacuate the city. The first prevents the risk of homelessness and the second the risk of mass casualties. The situation model embeds both. For the Projected model, however, it depends on the projection time chosen by the user. Here, if $t_p = 48h$, the projected model will only embed the risk of mass casualties; it is going to assume that the accommodations will be set up at this time and, therefore, the risk of homelessness prevented. This second step is part of the Environmental impact

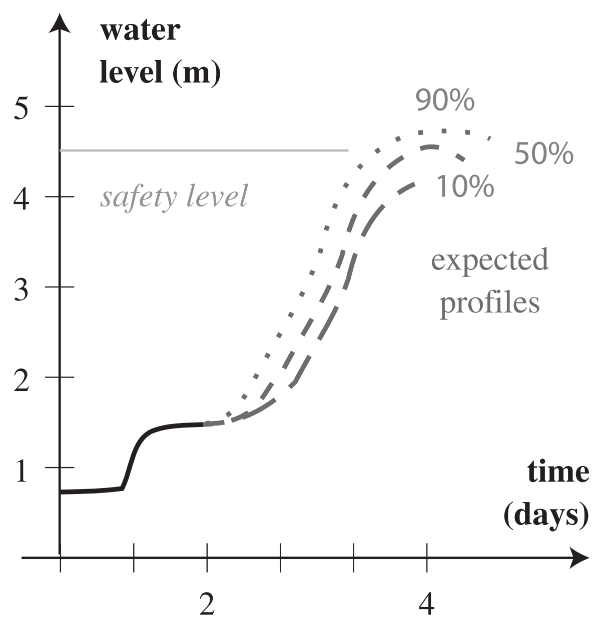

Figure 9. The profile of the Loire River (water level) inspired from the work of the SPCs: the French flood forecast services.

assessment, as defined by Glasson, Therivel, and Chadwick (2013): it models environmental implications of a proposed action.

Then, for each projection time wanted by the user, the Simulation engine recovers the value of the profiles stopped at t_p and updates the Projected model with new information deduced by the same complex event processing rules as before. For example, if $t_p = 48h$, the Simulation engine will reach for available forecasts given by the Learning engine or dedicated Web services. In the case of the profile given in Figure 9, in 48 h, the safety level of one city (Orleans) has 50% chance of being reached. Thanks to this information, the following complex event processing rule (Equation (2)) will ask for the addition of an Effect of dyke failure in the Projected model at t_p. This addition will trigger the next complex event processing rule (Equation (3)) that will add an effect of submersion for every building represented in the Situation model and protected by the dyke.

$$\begin{array}{l} \textit{Event topic} : \textit{Water Forecast Event} \\ \textit{Model} : \textit{Projected Model} \\ \text{IF the water level in a (city)} > \text{safety level of the (city)} \\ \text{THEN add on the (model) the Effect}'\text{(city) dyke failure}' \end{array} \tag{2}$$

$$\begin{array}{l} \textit{Event topic} : \textit{Add Node Event on a Model} \\ \textit{Model} : \textit{Projected Model} \\ \\ \text{IF Name of Event} =' \text{(city) dyke failure}' \\ \text{AND IF} \ \exists \ \text{(building) as a sensitive building} \in \text{(model) SUCH AS (building)} \in \text{(city)} \\ \text{THEN add on the (model) a Risk}'\text{(building) submertion}' \\ \text{on every (building)} \end{array} \tag{3}$$

The two event processing rules above apply on events emitted under a topic specified on the first line of the equation. The second line of the equation specifies the model in which an instance has to be added, updated or deleted. Here, because the Interpretation engine analyses forecasted events, the rules apply to the Projected model.

4.4. How to communicate information on the ongoing crisis or its anticipated future to the crisis cells?

The Visualisation engine, the module at the centre of Figure 6, updates the user interface: a common operational picture, as described by Dickinson (2013) and as recommended by the American national response framework FEMA (2008). It takes the shape of a geographical information system as recommended by Dawes, Cresswell, and Cahan (2004), to improve situation awareness inside a collaboration as specified by Sun and Li. (2016). This uses the fact, underlined by Luokkala and Virrantaus (2014), that almost all relevant information in crisis management missions is spatial. The goal of the visualisation engine, updating the common operational pictures, is to aggregate available information according to the specificities of its users, in order to reduce information load and ease understanding.

First, the *Visualization engine* needs a meta-model where each concept is marked with a boolean: if the concept concerns the current user, given its role in the current crisis collaboration, it is marked as 1. This task is done once, during the preparation phase,

Figure 10. Example of common operational picture, suited to the lowest crisis cell inherited from R-IOSuite developed by Salatgé et al. (2019).

before the crisis. For example in France, the Role of one *Partner* (cf. Figure 7) may correspond to one of the hierarchical levels shown in Figure 1.

Then, the *Visualisation engine* uses the marked meta-model to create a suited view of the current *Situation model* and *Projected model*. Each view corresponds to a common operational picture shared inside one of the crisis cells involved. Therefore, a mayor will neither see nor access the same information as the Prime Minister. For instance, Figure 10 shows one common operational picture suited for a crisis cell of the county level. The danger areas are in light grey, the damage areas in dark grey and the buildings at stake, as a hospital, are represented with icons.

5. The effects of the proposed architecture on the 5vs of Big Data

The following section describes the effects of the proposed architecture on the 5Vs of Big Data. Figure 11 locates each result, described below, in the proposed framework. Each situation awareness level, represented in the first column, is reached thanks to a specific object. The proposed architecture perceives the crisis situation through the update of the Situation model. It reaches the comprehension level by (i) connecting to R-IOSuite and (ii) deducing a response process suited to the current situation. Finally, it understands the crisis situation through the update of the Projected model. Figure 11 completes Figure 5 at a lower level of abstraction.

5.1. How the proposed emergency decision support system controls the volume?

The streams are selected by topic, filtered and aggregated in order to decrease the volume of incoming events. In addition, the common operational pictures drastically

	VOLUME	VELOCITY	VARIETY	VERACITY →	VALUE
UNDERSTANDING Projected model [Proposed architecture]	inherited from the perception step	forecasted events processed as soon as they are published & projected model updated within few minutes	inherited from the perception step	same complex event processing rules used (as the perception) & multiple sources by topics	events transformed into complex events updating the projected model & information editable by users
COMPREHENSION Response process [RIO-SUITE]		suited response process deduced within 2min by RIO-SUITE	process following the business process modeling language & tasks given by the experts of crisis management	inherited from the perception step	process editable by users & process orchestratable by RIO-SUITE between stakeholders
PERCEPTION Situation model [Proposed architecture]	event streams selected by topics, filtered by conditions	events processed as soon as they are published & situation model updated within few minutes	events published under the web service notification standard & information following a metamodel common to all stakeholders and all kind of crisis	complex event processing rules validated by experts & multiple sources by topics	events transformed into complex events updating the situation model & information editable by users

inherited   important   critical

Figure 11. The results of the proposed architecture given the proposed framework.

decrease the volume of information communicated to the users inside the crisis cells by adapting to each hierarchical level's needs.

5.2. How the proposed emergency decision support system controls the velocity?

The events are processed as soon as they arrive and both the timestamp and the description of an event are used to evaluate the expiration date of a new information that can be modelled on both the situation model and the projected model. Therefore, it takes only minutes to interpret new events and update the visualisation of the Situation model, the Projected model and, if required, the Response process proposed by R-IOSuite.

5.3. How the proposed emergency decision support system controls the variety?

The WS-N protocol followed by all our event sources erases the variety issue for all incoming events. In addition, the Situation model and the Projected models instantiate a meta-model designed to support collaborations. The meta-model follows the W3C web ontology language recommendations, through the use of XML (Extended markup language) contents. The proposed meta-model completes the R-IOSuite meta-model with a layer dedicated to crisis management (cf. Figure 7) thus avoiding interoperability issues between the two systems. Among these concepts, some are essential for floods (Water), storms (Networks), or industrial accidents (Buildings). Besides, the meta-model frames the Situation model and the Projected model perimeter and limits the variety of all the information stored in the proposed decision support system.

5.4. How the proposed emergency decision support system controls the veracity?

All the complex event processing rules have been validated by an expert during the preparation phase before the crisis. Additionally, each topic conveys data from multiple sources. The same complex event processing rules are used to update the Projected model and do not need to be validated twice: this is one of our main contributions.

5.5. How the proposed emergency decision support system obtains value?

The interpretation engine turns incoming events (data) into Situation model's instances (information). It uses R-IOSuite to deduce a suitable process to respond to the crisis (knowledge) and it turns forecasted events into Projected model's instances (understanding) thus ascending the pyramid presented in Table 1. In return, R-IOSuite benefits from the Projected model to deduce even more accurate response process. By following the same idea, the method developed by Barthe-Delanoë et al. (2014, 2018) to detect when the expected situation deviates too far from reality could use the Projected model to increase the agility of an ongoing response process.

In addition, the proposed meta-model, based on the practitioners' expectations, boosts the usefulness of the stored information, while the common operational picture enables the user to manually update the Situation model, the proposed response process or the Projected model.

6. Conclusion & perspectives

The business issue – *BI* – and the main problem – *P* – raised in the introduction: The crisis cells need support to ensure (i) the consistency of the decisions between the different hierarchical levels, (ii) the coordination of the actions requested from the services involved in the response and (iii) the communication of the right information, at the right level of detail for the right person, at the right time. What type of architecture should be set up to enable a decision support system to continuously climb the three levels of situation awareness, display activable information on a common operational picture inside each crisis cell, while managing the volume, variety, velocity and veracity of the data processed to obtain new information in order to improve the value of the resulting situation awareness shared inside the crisis cells?

To answer this problem, and therefore the business issue, we have followed a dedicated methodology:

(1) We identify a framework, that can be followed by every decision support system willing to enhance the situation awareness of their users or their system, by connecting to new, external, data sources;
(2) We identify several existing works in each part of the proposed framework, but none of them was able to manage all the 5Vs of Big Data while ascending the three levels of situation awareness.
(3) We identify four proposals to be followed by every decision support systems willing to enhance a situation awareness through the connection of new external data

sources: the model-driven architecture; the event-driven architecture; the Web services notification standard and the machine learning.

(4) We design and implement a new emergency decision support system architecture that follows the proposed framework. Therefore, it can support the three levels of situation awareness of its users by automatically perceiving, comprehending and understanding a crisis situation, while managing the 5Vs of Big Data.

Our main contribution is the proposed architecture, as an answer to the business issue and the main problem raised in the introduction. One additional contribution involved the design and implementation of a complex event processing engine able to query our models (situation model and projected models). It is therefore able to perceive its own situation before updating its representation in the system.

As a result, the proposed architecture is implemented, inside the R-IOSuite tool suite, and available, as an open-source project, for https://R-IOSuite.com/display/RIOSUITE/Binariesdownloads[2]. A https://R-IOSuite.com/display/RIOSUITE/Demo+Videovideo[3] of the River Loire flooding use case is also available under the name 'Use case Loire Flooding'.

This lays the foundations for future decision support system dedicated to support complex decision-making, in unstable environments, like crisis situation or battlefields. In future studies, further research could:

- Evaluate the strengths and weaknesses of the proposed framework. For now, it prevents researchers to forget one of the 5Vs of Big Data while placing their research on one of the three steps of situation awareness;
- Compare the results obtained by the proposed decision support system, to other emergency decision support systems, in terms of reactivity (time between the reception of an event and the update of the common operational picture) and effectiveness (difference between one user's situation awareness with and without the decision support system support);
- Test the proposed emergency decision support system with challenging incoming data, coming from social networks, where issues related to the veracity, velocity and value are particularly present.

As a final thought, the proposed emergency decision support system architecture could be used in a manufacturing context, where industries aim to improve their agility in ever more unstable environments. They indeed have the opportunity to access huge amounts of data Jiang, Lamothe, and Benaben (2017), including their own *internet of things*. Thanks to the proposed framework, they will be able to implement new decision support systems, without neglecting problems related to the volume, variety, velocity, veracity or value of their data, information and knowledge.

Notes

1. Third Edition, p528.
2. https://R-IOSuite.com/display/RIOSUITE/Binaries.
3. https://R-IOSuite.com/display/RIOSUITE/Demo+Video.

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