Understanding the new Context of Uncertainty and Risk under the 4th Industry Revolution

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The revolution towards the Industry 4.0, requires as a fundamental challenge the advanced treatment of risk in physical assets according to this new context. This revolution also includes the transition towards a new concept of assets and production systems giving rise to those known as cyber-physical systems (CPS) where the available information and knowledge about the systems and its behaviour should promote a level of control of the risk not known until now. In this context, the transition from classical model for risk management to other concepts, more flexible and dynamic is needed. It is the context that this paper is intended to illustrate, approaching risk control to the available data and technology.

Keywords: Asset, Digitalization, Industry 4.0, Risk, Uncertainty.

1. Introduction

The industry transformation with the new technologies is a process in constant evolution. Traditional industrial scenarios will change with an intensive and aggressive use of internet technologies. The main idea is that bringing the support of innovative technologies inside the industrial field will give the manufacturing sector a chance to perform a proper revolution: gain of productivity, revenues, knowledge, etc. This vision has been materialized in the scientific community across the proposal of a series of concepts that serve, somehow, to guide this development: Smart Factories, Factory of the Future or Industry 4.0 are some examples. But, in the last recent years, Industry 4.0 has been definitely adopted as main reference.

Industry 4.0 requires, as one of its principal challenges, a proper evolution of risk control and, in a more strategical view, the own evolution and generalization of the Risk Management System. Risk control will play a relevant role; in particular, its importance is growing through the years for the raising and necessity of product quality and system safety (Aven, 2012). Above all against the background of increasing complexity, the growing number of objects and the increased use of a wide variety of technologies, risk analysis should be prepared for these changes (González-Prida & Zamora, 2019). This document is a kind of State of the Art, whose ambition is to discuss about uncertainty in risk control given the available data and new technology (Industry 4.0 revolution). Throughout the paper, technological developments will be presented and comment

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with reference to relevant literature on risk management and uncertainty.

2. Intelligent Risk Management as a Key Factor of Industry 4.0

An Industry 4.0 framework (Villar et Al., 2018) will make possible to gather and analyse data across machines, enabling faster, more flexible, and more efficient processes to produce higher-quality goods at reduced costs with a high-level control of risk (González-Prida et Al., 2018). Most of the advances that new technologies supporting Industry 4.0 framework are directly related to provide new instruments for a more efficient (real-time, knowledge based) risk assessment, which is actually the key concept of smart decision making. Within these reference technologies, considered as Industry 4.0 pillar, can include the following:

- Big Data, the amount of data extrapolated from the assets (e.g. health condition, production parameters) (Lee et Al., 2014). Big data applications have a direct link with intelligent risk management conception. Actually, risk evaluation can be performed when there is great amount of data and there is no previous experience or reference models. Something similar can be said about the below mentioned technology.
- Data Analytics/Mining (i.e. algorithms used for the interpretation of raw data extrapolated from the asset) (Alexandru et Al., 2015).
- IoT (Internet of Things), an expression that includes a great amount of meanings, possibly reassumed to the extension of internet to concrete object (Alexandru et Al., 2015). Talking about Industry, IoT concept is the promise of total risk control. IoT talks about real time, connection, knowledge, etc. And it means that machine itself knows very well the risks being proactive man-aging them.
- CPS (Cyber-Physical Systems), the new way to describe a renewed reality where a machine is not only represented by physical features, but also the cyber ones, where a perfect digital clone of machine is created and stored in a cloud for further analysis, playing a central role in the revolution for its flexibility of application and amount of exploitation possible (Henning et Al., 2015).
- PHM (Prognosis Health Management) is a key research area that has leveraged on advanced predictive analytics to transcend traditional risk control practices (Guillén et Al. 2016). PHM is currently a very active research field due to the motivation to have a more objective assessment on the true condition of production systems (Lee et Al., 2013). With the latest progress in data analytics and information technologies, that degradation is visible, and, using algorithms and analysis methods, information about machine Health and Remaining Useful Life (RUL) are obtained; it is possible to schedule the activity only when really needed, and to exploit machines till their real capacity (Lee et Al., 2006). A risk evaluation incites a process that enrich the own risk analysis combining different interpretation options and making conclusion from that. Comparing this risk assessment with prognostics results will be the next step. Even it is possible to argue that in order to know if PHM solution is really feasible in a real industrial application, PHM application effects should be compared with other risk assessment method.
- Ontologies & Semantic: Ontologies are rapidly becoming popular in academia. There is a tendency both in converting existing models into ontologies and in creating new models. Ontology models support several useful features, where the main ones are: to share common understanding of the structure of information among human or/and software agents; to enable reuse of domain knowledge; to make domain assumptions explicit; to separate domain knowledge from the operational knowledge; to provide formal analysis of terms and based on them, analyse the domain knowledge (Matsokis & Kiritsis, 2010). Finally risk assessment model have to be translated into the system ontologies description since, at the end, risk is one of the most important part of management and decision making. Approaching risk evaluation may provide an

open vision that contributes to understand the utility of this kind of models.

The vision of smart risk control refers itself as an enabler of Industry 4.0, keeping the cyber-physical systems (CPSs) efficient and available. These CPS present a high degree of networking, digitization, decentralization and autonomy. More in detail, the asset utilization has to be reformulated, exploiting the increased routing and machine flexibility, with remote control and monitoring of systems (Bughin et Al., 2017), and for the success of this challenge is crucial that new risk assessment tools are developed to allow validating and justifying the real impact of this technological change in the value management of the industries.

3. Uncertainty within the context of risk analysis

Many classifications of uncertainty have already been defined in literature. Of course, no classification appears as perfect, and it is often the consequence from particular theoretical argumentation and interpretation of probability. In practice, types of uncertainty often overlap and sources are mixed in a complex way. An uncertainty classification (Ferson & Ginzburg, 1996), (Hoffman & Hammonds, 1994), often found in the literature, is the following:

- Aleatory uncertainty, arising from the intrinsic variability of the process under study and it cannot be reduced by further measurements;
- Epistemic uncertainty, arising from the lack of knowledge about the parameters characterizing the physical system.

The term aleatory uncertainty describes the inherent variation of the physical sys-tem. Such a variation is usually due to the random nature of the input data, which can be mathematically represented by a probability distribution once enough experimental data are available. On the other side, epistemic uncertainty is due to ignorance, lack of knowledge or incomplete information.

Identification of uncertainty sources is the key to develop a general methodology to assess such an uncertainty. Uncertainty quantification is a challenge and re-searchers have proposed different mathematical models to adequately represent it. Traditionally, the probabilistic approach has been widely used to manage both uncertainties. However, such an approach requires known probability density functions, generated from historical data. Thus, representing epistemic uncertainty by probabilistic means is questionable because there is no reason a priori to prefer one probability distribution function over another which can be misleading. For this reason, a meaningful attention has been paid by researchers to theoretical approaches alternative to the probabilistic one. In particular, the Possibility Theory (Zadeh, 1978) and the Evidence Theory (Shafer, 1976), also known as Dempster-Shafer Theory (DST), have been considered as the most promising methodologies to deal with the epistemic uncertainty.

Moreover, uncertainty modelling can be important to understand how the input uncertainty has propagated to output uncertainty. Formally, it is sufficient for a model to link the important output variables of interest to a number of continuous or discrete inputs that can be uncertain, subject to randomness, lack of knowledge, errors or any other sources of uncertainty or fixed, namely considered to be known (Rocquigny et Al., 2008). In addition to uncertainty handling and modelling, reducing data uncertainty as much as possible is necessary in order to obtain precise and reliable results. Some research problems have just tried to study this topic and develop methodologies, applying them in other contexts as well as diverse problematics that have been thoroughly discussed in the literature (see for example: Bjerga et Al., 2016; Shortridge et Al., 2015; Aven & Renn 2009; among others).

Sensitivity analysis plays a key role regarding how to communicate the shortcomings and limitations of probabilities and expected values (Flage & Aven, 2009). It is usually con-ducted in order to examine the standard error caused by estimation process (Ratto et Al., 2001), (Saltelli et Al.. 2004). The approach used in reference (Ratto et Al., 2001) is based on a direct decomposition of the model output variance into factorial terms, called "importance measures". Sensitivity indices are computed by dividing the importance measures by the total output variance. These indices represent the expected amount of variance that would be removed from the total output variance if the true value of individual input variable is known (within its uncertainty range).

In this regard, uncertainty in reliability characterization is also associated with censoring point, as well as an initial sample size. This situation can be solved by using big data or by the generation of simulated values. Monte Carlo simulation is usually applied to determine the minimum sample size, as well as the earliest censoring point for accurate reliability assessment. This simulation is designed to determine the earliest censoring point associated with test duration according to initial sample sizes, which provides the right balance between censored and failed sample sizes without compromising uncertainty in reliability assessment.

4. Conclusions

The rapid development of technologies like Big Data techniques, methods, and their applications, is leading to the use of advanced methods for reducing uncertainties which allows controlling the risk level with which a system operates. As commented in reference (Guillén et Al. 2016), Big Data solutions implicitly cover a complete process, from capturing the raw data up to utilizing the information for decision-making, improving consequently the uncertainty management. Nevertheless, regarding the analysis of the risk associated to consequences under high levels of uncertainty, the knowledge and information available for that analysis is questionable that can be reflected properly by probabilities (Flage et Al., 2014).

This document has been intended to bring out some central themes and definitions of technologies, introducing somehow the actual contribution beyond technology and risk. Future research lines would benefit the topic, deepening in the methods or models, providing examples of such approaches and showing how they can be formalized. An appropriate uncertainty management would allow more accountable forecasts, better natural and industrial risk control, and more robust performance for improved system designs among other benefits. Particularly, starting from available input data, the purpose here has been to underline the importance to control uncertainty propagation from inputs to outputs and, thus, to refine the decision making. With the acquired information, it will be possible to obtain results more precise, allowing to decision makers to take more correct actions in order to select appropriate risk control policies.

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