Addressing Uncertainties in Complex Manufacturing Environments: A Multidisciplinary Approach

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Abstract. With the introduction of intelligent and autonomous systems into factory environments, workplaces where human employees work alongside digital counterparts will become increasingly informational. We develop a generic framework for hypothetical workplaces to investigate how complexities create to uncertainties. Complexity may be explained through the Level of Abstractions used to model a system, and it is encountered in its dynamic form as an alteration of information flow between agents in a phenomenological relationship. Analyzing these systems as 'information flows' brings to light the uncertainity(ies) the workers of the future will have to cope with. We develop first concepts that can be used to develop heuristics to manage these uncertainties in complex manufacturing environments. These heuristics may also be useful in creating optimized workplaces that combine the individual abilities of both humans and machines. The framework proposed in this paper may be subject for an empirical validation of these heuristics in the future.

Keywords: Uncertainties · Complexity · Human-machine interaction

1 Introduction and Motivation

In this paper, we propose a conceptual framework that can help us identify and manage the causes of complexity and uncertainties in future manufacturing systems [25], especially in the context of Industry 4.0 [26]. Both uncertainty and complexity have been dealt with on their own in the past, and it is generally accepted that the complexity of manufacturing systems is increasing [30], and that this complexity needs to be reduced if we wish to increase the applicability of such systems [29]. At the same time, the nature of these systems is also increasingly informational, therefore the exchange and interpretation of information dominates how humans interact with these systems [28]. This relationship is not one sided; we need the machines as much as they need us as humans are the only semantic engines in existence [15], and as long as technology is designed to serve human needs, the idea that "Man … has the function of being the permanent coordinator and inventor of machines that surround him" [3] only seems to be reinforced. "Far from being the supervisor of a group of slaves, man is the

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permanent organizer of a society of technical objects that need him in the same way musicians in an orchestra need the conductor" [3], the difference being that instead of interpreting musical notes in a symphony, here one needs to interpret information as it constitutes complex systems and processes, and these systems and processes tend to be integrated, simultaneous and decentralized [1].

As we elaborate in this paper, the nature of complexity is the nature of interpretation of information, and the situations and contexts under which this interpretation occurs creates a multitude of uncertainties. Time and again, incidents throughout history exemplify the role of complexity in endangering human safety, or in reducing our sense of security as a new form of technology threatens to replace us. As long as new technology is created to serve human needs, we believe that the development of Human Machine Interaction, especially in the context of Industry 4.0 will not be fruitful without addressing the cause and nature of complexity and uncertainties, as well as means to address them. At the end of the paper we provide metrics, which aim to measure these causes and develop heuristics and empirically proven strategies in the future.

2 Definitions of Key Terms

In order to address complexity and uncertainty, we will draw from various disciplines, including Philosophy of Technology, Information Science, and the Philosophy of Information. We apply the terminologies to human computer interaction in general – but we focus on applications in the manufacturing context. Several key definitions are defined here to avoid repeating them in further sections.

It has been argued that the nature of human machine interaction is *situated* [32], for the scope of our discussion a situation may be 'determined by a topologically simply-connected, structured region of space-time' [19].

Every situation exists in a particular *context*, which can be described as "the set of interrelated conditions in which a situation occurs, what can be described, informally, as the immediate environment of a situation or, topologically, its neighborhood [15]. Hinton defines context as "an agent's understanding of the relationships between the elements of an agent's environment" [20].

In order to comprehend and describe any complex phenomenon, some kind of abstraction is needed. For our purposes we use Floridi's method of the *Level of Abstraction* (LoA), where a LoA is "a finite but non-empty set of observables". An "observable is defined to be a typed variable together with a statement of what feature of the system under consideration it represents" [17]. Depending on the purpose, different LoAs may be necessary. For instance the manufacturer of a temperature sensor may use an LoA that defines its temperature range, data speed, distance range etc., whereas a system designer may use an LoA that consists of cost, reliability, energy usage etc.

Since we are also concerned with the semantic interpretation of information in complex systems, we rely on a formal definition of the notion of '*semantic information*' as 'data that is well formed, meaningful, and truthful', where truthful is used to mean 'providing true contents about the modeled system' [15]. This definition requires the presence of a rational agent or observer who can *verify* and *validate* the correctness of data with respect to an anterior system. Any given message will be true in a *context*, at a *LoA* for a particular *purpose* [16].

The functional and informational aspects of complex systems are intertwined. Xing and Manning [13] propose that complexity is the combination of three basic factors – *quantity* of basic information elements in a system, *variety* of elements, and the *relations* between elements. Further, they identify two principles, which play a role in complexity, the first being the principle of *observer dependency*, which says that "Complexity only makes sense when considered relative to a given observer" [13]. The 'observer' here is similar to the 'agent' in the definition of context. The second principle is that of "*task dependency*, that is, the complexity of things depends on the task". Deshmukh et al. [22] described two forms of complexity – static complexity owing to "structure of the system, connective patterns, variety of components, and the strengths of interactions, and dynamic complexity, described as "unpredictability in the behavior of the system over a period". Li and Wieringa [5] proposed a framework of 'perceived complexity' that takes into account the human-machine system complexity, task complexity, personal factors, and operation and management strategy. ElMaraghay et al. take an informational approach, where complexity depends on the diversity, content and quantity of information needed for a task [23].

In the context of Industry 4.0, we view complexity as cyber-physical in nature, since in these systems information and physical behavior are coupled and participate in information exchange and feedback. Nonetheless, in our view the final mode in which complexity is encountered remains informational, since the only way agents can perceive and interact in systems is via an exchange of information.

In Information Science, the effectiveness of this exchange of information is characterized by the notion of *relevance* which is considered as a "relation between information or information-objects on the one hand, and contexts which include cognitive and affective states on the other hand, based on some property reflecting a desired manifestation of relevance [24]. Floridi [15] defines relevance in a purely informational sense, where an information i is relevant to an agent a w.r.t. domain d in a context c at a given LoA l iff i satisfies q as an adequate answer. Shutz [8] defined a stratified, interacting system of *thematic* (perception of a problem), *interpretational* (grasping the meaning of that which is perceived based on stock of knowledge at hand) and *motivational* (the purpose of the action) relevances. Regardless of the definition chosen, one may observe that relevance qualifies information exchange, that is, it appears only in a dynamic system.

Finally, we define the concept that most concerns us. Uncertainty has been discussed in various disciplines over centuries, and there are many definitions of uncertainty, but at its core, uncertainty pertains to a lack of information. We use Floridi's concept of uncertainty, where "Uncertainty is what a correct answer to a relevant question erases" [15]. In other words, as long as an agent a does not have a relevant answer to a query q about domain d in a context c at a level of abstraction l, a is in a state of uncertainty. According to this definition, uncertainty ties all the concepts defined into an informational relationship except complexity, whose relationship to information we discuss in the forthcoming sections.

3 A Model of Complex Manufacturing Systems

Automation is the first property of manufacturing systems that shows an increased amount of complexity. The traditional model of automation consists of a hierarchy of layers, each layer building on the next, where information flow takes place between the layers. The development of cyber physical systems (CPS) shifts the structure towards a distributed model [4]. Broy describes cyber physical systems as an onion-layered model of a 'system of systems' [1]. Monostori uses a network model to illustrate an ecosystem of distributed services [2], and also highlights the roots of CPS: Intelligent Manufacturing Systems, Holonic Manufacturing Systems, Reconfigurable Manufacturing Systems, Digital Factories etc. While a deeper study of the differences between these systems is outside the scope of this paper, we abstract a general model.

A machine agent consisting of connected components executes a physical process. A digital model of the said process is constructed by means of information exchange via sensors and actuators. Process control is exercised through some level of automation that determines the amount of human machine interaction. Multiple agents can be linked together through the use of networking, and information processing between various processes allows for a creation of a node that can then connect to other nodes creating larger, socio-technical constructs.

The digital model can be considered to be a *proxy* of the physical process; hence we end up with two agents of information processing in this model. The machine agent facilitates information flow in a process and at the same time exchanges information with a human agent via the use of this proxy, which means that the behavior exists in two contexts, one of machine agents and the other of human agents (Fig. 1).

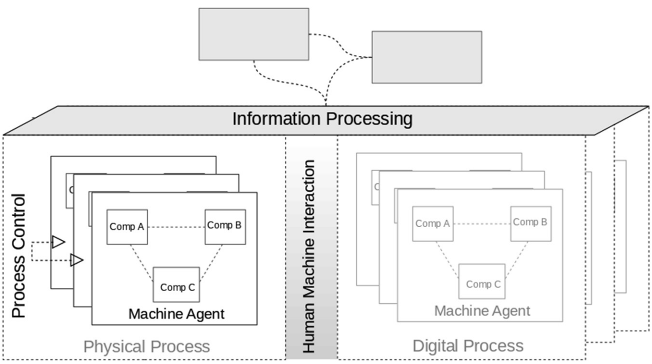

Fig. 1. General model of a digitalized manufacturing system.

4 Defining the Machine and Human Contexts

In this part we define the two contexts in which human machine interaction occur. The focus here is to define the structural properties of these contexts, in the next section we look at dynamic behavior.

The *machine context* refers to context in which information flows in a technological system. We use the LoA concept to describe machine complexity as one resulting from system of nested LoAs. Manmade systems are typically designed to serve a purpose, and from their conception to implementation, they go through many different stages, each of which involves the establishment of a particular LoA. Each "lower" stage is more *specific* than the previous, which is, each stage, in order to more precisely define the system, increases the number and nature of observables involved. For instance, a simple switch when seen at the most abstract level may consist of only 2 states {*on, off*}, but the subsequent stage can consist of electrical {*5v, 0v*} and mechanical variables {*contact, no contact*}, which can then be further described in terms of tolerances, material properties and so on. The relationship is illustrated through the diagram below (Fig. 2):

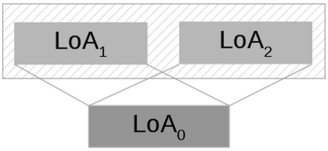

Fig. 2. The abstracted view represented by LoAs.

The abstracted view at LoA_0 is described by two the non-overlapping LoAs, which are themselves chosen to represent the required observables from a possible space of observations. This choice itself can rely on many factors, for instance customer requirements, cost constraints, designer's level of experience etc. Now, we assume a system that consists of multiple components, which are chosen to collectively fulfill a purpose. The highest level of the system can again be abstracted to offer the simplest definition, but now the system itself consists of multiple LoAs that co-exist in the same context (Fig. 3):

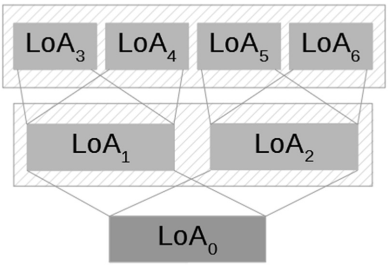

Fig. 3. Extending the LoA relationships to describe a system in more detail.

In this case, a seemingly simple relationship between 2 components at LoA_1/LoA_2 is behaviorally represented by a Cartesian product of the observables in LoA_3 to LoA_6. As a result, the number of possible situations in which a system exists increases, as does the complete observation space. Since “the model of a system is a function of the available observables” [18], if a system consists of more observables than are chosen, there is a discrepancy between the model of the system w.r.t the system itself. The following possible ‘axioms of the machine context’ can be deduced:

(a) *When a component brings in observables that are extraneous to the system at hand, it models more than what’s needed (“overspecification”)*
(b) *When a component consists of an insufficient set of observables, it models less than what is required (“underspecified”).*
(c) *The chosen LoA determines the model.*
(d) *In order to have a complete, accurate and precise description of a system a model is needed where information flows within and in between each LoA is available.*
(e) *Each component is a system in itself, chosen to model an aspect of reality that, to the extent of our knowledge, plays a functional role in the system.*

Ultimately, information flows are obstructed between nested LoAs if the observer gets to see only a particular LoA, which hides system description. Interruption of information occurs when the observables themselves overstate (resulting in ambiguity) or understate (resulting in errors and exceptions) the possible situations in which a system can exist. Thus, uncertainty is intrinsic (‘baked into’) any design of systems.

The *human context* encapsulates the context of the human observer who discovers, encounters, and interprets information. In the domain of manufacturing systems, Li and Wieringa note that “the perceived complexity is not only the reflection of objective complexities, but there are also other factors that affect perceived complexity” [5]. They further classify two factors: personal factors, such as “intelligence, knowledge, job training, personality, cultural background, and willingness”, and the organizational factor, that is, the “operation and management strategy that has been designed for the operator or developed by the operator himself”. Park mentions “aptitude, intelligence, ability and cognitive style of a qualified operator” along with “domain knowledge” as some of the factors involved [6]. Pekrun et al. highlight the emotional aspect of understanding information, which they define as epistemic emotions [7]. We identify here the following ‘axioms of the human context’:

(f) *Some form of a mental model based on domain knowledge and training.*
(g) *A motivational aspect, which depends on personal goals.*
(h) *An affective aspect in dealing with information.*
(i) *A cognitive aspect of the individual to grasp new information and integrate it into existing knowledge.*

5 Information Flows and Meeting of Contexts

In this section we introduce our framework that looks at how an exchange of information between these contexts may explain the relationship between complexity and uncertainty. We follow the phenomenological tradition and make use of Ihde’s [9] post-phenomenological concepts to explicate the relationship between humans and technical artifacts in terms of information flows.

5.1 Information Flow as a Phenomenological Relationship

An information exchange is also a relationship, as long as we are concerned with *mediated relations* between humans and technological artifacts, as elaborated by Ihde [9]. Since most control interfaces are a representation of the actual process, an interpretation is required; hence the relation qualifies as *hermeneutic (in a philosophical sense)*. This relation is directed from the machine to human context. A second type of relation that Ihde mentions is one directed from us humans towards machines, the *alterity* relation. Since we live in a socio-technical environment, *background* relationships shape our environment unconsciously. In case of automated systems the context is created without an active involvement of the operators. This relation may gain importance as supply chains and factories become increasingly automated, and is shown here as a socio-technical context.

Based on this post-phenomenological approach, in Fig. 4 we consider the paths of information exchange in between the different contexts, and use them to construct the key points of this paper. Case 1 illustrates an ideal information flow that is well defined in its path and relationships between the different LoAs. A non-ideal information flow exists in the following situations:

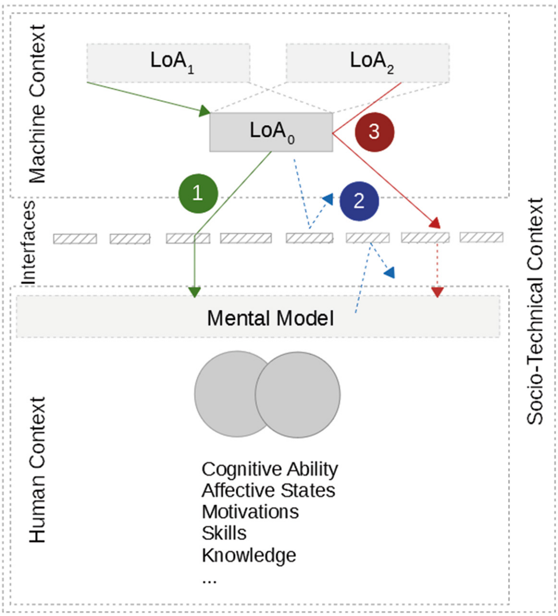

Fig. 4. Modeling the different contexts and information flows.

(a) **Proliferated Flow:** In a normal scenario, the quantity of information can be represented by the number of different interfaces an agent is interacting with. In special scenarios, it is seen as a case of 'LoA intrusion' - the underlying LoAs are revealed unintentionally, often with a higher degree of information flow and variety – information overload is a typical example. A possible case is a situation where the information in the socio-technical environment is transferred directly to the machine context, for instance intelligent systems responding to the market conditions. Case 3 represents such an 'information jump'.

(b) **Inhibited Flow:** Represented as a case where information is sought but not received, or the case where the human agent intends to convey what is considered to be relevant to the situation but the information is rejected by the machine context. This can be seen as Case 2.

(c) **Interrupted Flow:** Any natural or man-made component is subject to unavoidable failure due to wear, or due to programming errors. In the former, information flow may stop entirely, while the latter creates an exception. For example, information flow in Case 2 depicts a case where a machine's internal state results in an exception that is redirected back to the human context.

(d) **Alterity Flow:** In any form of human-artifact interaction, humans tend to project anthropomorphic properties onto objects [10]. In a factory environment the cognitive and affective state of an operator can play a role in how the information is interpreted and reacted to.

In terms of human-machine interaction, all the cases above manifest themselves as issues of "relevance" as defined previously. The agent expects a particular response to a query in the context of solving a problem, and if data is directed at an agent, it will not be relevant unless it fulfills a purpose for the agent – as Schutz mentions, at a *thematic*, *interpretational* or *motivational* level [8]. Similarly, data received at the machine interface is accepted only if it fits into the algorithmic purpose of the interface. A human agent inevitably has cognitive and affective states involved in the flow of information, influenced both by the background and the human-machine interaction in a particular context.

5.2 Relating Information Flows to Uncertainty

Here we elaborate on the various forms of uncertainties as induced by the characteristics of information flows. Some of these have already been discussed in literature [11, 12]:

(a) **Proliferation Induced.** Proliferation here is meant in the sense of the inopportune spatio-temporal nature of information explosion in. For instance, *volume induced overload* is a major topic of research, shown to increase uncertainty through "numerosity (the number of separate elements to be dealt with), diversity (the range of information sources and media), and inter-dependence (the complexity of causal relationships between the information elements)" [11]. In the temporal sense, acceleration can also induce *temporal uncertainty* since information can flow near instantly, may be present at the same time at different devices, and may require time bound intervention by operators. An alarm flood is a typical example. Network behavior may exhibit both the effects simultaneously, for instance, product placement on social media platforms can create fluctuating patterns in product demand, translating to production uncertainties.

(b) **Inhibition Induced:** To inhibit, according to the Merriam Webster dictionary means to "prevent or slow down the activity or occurrence of something". A lack of information either in the desired quantity or at the desired time is generally classified to create three different forms of uncertainties. First, *epistemic uncertainty,* where the information is not relevant or accurate enough to explain system behavior, second, *alethic uncertainty,* where the truthfulness of information cannot be verified – without a sufficient knowledge of the system that can act as a proxy to the system under observation, and thirdly, *skill uncertainty,* where on one hand more and more information is inhibited in everyday operation due to automation, and on the other hand more variety of operations are introduced to be carried out by the same workforce. The irony in the classic paper "Ironies of Automation" [31], can also be understood informationally as the scenario in which an informationally inhibited system breaks down, exposing the underlying complexity and resulting in an information overload.

(c) **Interruption Induced.** Also known as *aleatory uncertainty,* which represents the unknowns in any system, which may result in component failures. This form of uncertainty is the focus of predictive statistical models and anomaly detection algorithms.

(d) **Human Induced.** While it may be possible to generally categorize patterns of human behavior, as is the focus of the study of human decision-making under uncertainty, the exact decision that a human operator will take under a given situation in a context is still somewhat uncertain due to the variety of psychological and physiological factors involved. The term *Volitional uncertainty* encapsulates the fact that human decision making is uncertain, as is our cognitive ability to understand information in a given situation, and secondly, *motivational and affective uncertainties* arise because moods and motivations cannot always be predicted accurately. These are active areas of research in cognitive science, but for the scope of our paper it suffices to identify this uncertainty.

6 Concepts to Manage Uncertainty and Complexity

In this part we propose concepts that can be used to further develop heuristics to manage complexity and uncertainty. As described in Fig. 4, a complex system consists of the physical process and its modeled digital representation in various LoAs, the highest level of which is presented to the user (LoA_0), both for the physical process and its digital twin. Interaction with the system takes place at the system boundary, where multiple devices may allow information exchange (shown as green arrows). The human agent interacts with the system based on a mental model of this system, either learned beforehand or via interaction with this system. The socio-technical context influences both the design of systems and the actors who take part in this interaction.

The proposed concepts are based on causes of uncertainties as identified in Sect. 5.2, and the axioms developed in Sect. 4, and categorized under the three interacting parts of as shown in Fig. 4, that is, the System, the Agent, and the Information Flow itself. In order to establish a scale to numerically assess the level of complexity and uncertainty in a given scenario of human machine interaction, we assign a value to different, measurable aspects of each component. Using these metrics, we also aim to classify the effects of different kinds of uncertainties on human and machine agents. While we may want to reduce some forms of uncertainty and complexity, other forms may be beneficial, even necessary, in the Human-Machine-Interaction loop. We hypothesize that our research will suggest that complexity and uncertainties need not always be *avoided* or *reduced*, but *optimized*, meaning that it may be desirable to aim for an optimal solution instead of a perfect one based on the effect these forms of complexity and uncertainty have on operators.

We would also like to state that the list here is not exhaustive, there may be more factors involved, and the list will be updated in the course of our research (Table 1).

Table 1. Metrics to measure the degree of complexity and uncertainty.

Name of Concepts	Description	Value
Machine Context		
Closeness between desired LoA and presented LoA	System observables at the interface LoA vs. user's expected observables.	Presented Observables divided by Desired Observables
Number of interaction devices	Points of information exchange	Scale from Low to Medium to High
Variety of interaction devices	Types of information exchange	Scale from Low to Medium to High
Information Exchange		
Openness of Information exchange	How much design information is available?	All/Some/Interface only
Degree of Connectivity	Number and types of connection nodes.	Isolated/Networked/Cyber-Physical
Human Context		
Subjective stock of knowledge	Classification of user level	Expert/Novice/Beginner
Motivational Level	Motivation as a component of information relevance and interpretation	Scale from Low to Medium to High
User Stress Levels	Interaction induced stress.	Scale from Low to Medium to High
Separation between design and use	Design involvement of the users	Designers are Users/System assembled from off the shelf components/System purchased designed and assembled

7 Conclusion and Future Work

In this paper, we presented a conceptual framework that bridged the domains of complexity, information and uncertainty. While complexity is tied to the Level of Abstractions used to model or explain a system, it is encountered in its dynamic form as an alteration of information flow targeted at or discovered by agents in a phenomenological relationship. We elaborated on the two contexts, the human and the machine context, which contain respectively the human and machine agents within which this relationship exists. We also identified properties of these contexts that we then used to develop concepts to quantify and relate the nature of information flow in the system to the amount of complexity and uncertainty of a complex manufacturing system. To make our investigation empirical, the next step will be to conduct empirical studies and develop testable hypotheses regarding the interdependencies of these metrics. These findings can lead us to heuristics that can be used to visualize and adjust information flows to select the optimal design strategy as well as hardware, software and UI techniques for developing manufacturing systems. With this technique it may also be possible to analyze ‘soft’ concepts like ‘responsibility’, ‘job descriptions’ and ‘spheres of influence’ in the workplaces of the future.

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