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Cross-Fertilization of Human-Systems Integration and Artificial Intelligence: Looking for Systemic Flexibility

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Abstract. Human-systems integration can advantageously use artificial intelligence to reach socio-technical flexibility. This paper proposes a systemic approach combined human and machine intelligence based on the shift from rigid automation to flexible autonomy. It emphasizes various issues, including maturity, life-critical systems (considering not only cognitive but also physical properties), systems as representations of people and machines, and the need to consider expertise and experience. It provides a deeper definition of the concept of system as a system of systems, represented by a network of systems where a network of functions could be dynamically allocated onto a structure of structures. The TOP model is introduced (technology, organizations and people). Three dual design and operations processes for human-machine function allocation are introduced: substitution/automation; amplification/interaction; and speculation/amplification. Three kinds of operational processes, leading to allocation of human and machine functions, are presented: procedure following that leads to automation of people; automation monitoring that results from automation of machines; and problem solving that involves coordination of increasingly-autonomous people and machines. This is precisely where AI could be efficient and effective by supplying tools that augment people's capabilities in problem solving. The overall approach has been coined "FlexTech".

Keywords: Human-Systems Integration, Artificial Intelligence, Systemic Flexibility, TOP Model, Autonomy, Automation, Function Allocation.

Human-Systems Integration (HSI) has been defined as a combination of Human-Centered Design (HCD) and Systems Engineering (SE), and an extension of Human-Factors and Ergonomics (HFE) and Human-Computer Interaction (HCI) [7]. John McCarthy and Marvin Minsky presented the first artificial intelligence (AI) program at the Dartmouth Summer Research Project on AI in 1956[1]. AI became big during the 1980s but did not go through until recently, leaving the field to HCI during the 1990s and 2000s. We can say that HCI highly contributed to human-centered automation. It is

[1] We should also give credit to Allen Newell, Cliff Shaw and Herbert Simon for anticipating artificial intelligence with the Logic Theorist, a program designed to mimic the problem-solving skills of a human and was funded by Research and Development (RAND) Corporation.

hoped that AI of the 2020s will contribute to the development of human-centered autonomy, which should greatly provide people and machines with appropriate socio-technical flexibility. Prior to introducing the potential shift **from rigid automation to flexible autonomy**, this paper presents a systemic approach of human and machine intelligence. Examples in the aerospace domain are given.

1 Thinking about systemic human and machine intelligence

During the 1980s, AI developed so much that we were thinking that it could invade our lives and replace people. Even if many people contributed to AI research, we experienced an AI winter during the last three decades! Today, AI resurrects even bigger than before. Should we be worried about being replaced by machines? Or, should we think in terms of interacting and collaborating with smart machines? The Cloud, for example, brings more autonomy to people than any tools had provided before. However, we need to be cautious. We should look after AI algorithms **maturity**. We should make sure that AI does not bring ways of doing things that are more complicated. Think about voice menus when you call a large company; you usually end up in being extremely frustrated just because the system is too rigid. This is because such voice recognition systems were immature for a long time.

What topics are currently main stream in the AI community? The 2020 AAAI[2] conference[3] proposes the following topics: search; planning; knowledge representation; reasoning; natural language processing; robotics and perception; multiagent systems; statistical learning; and deep learning. Summarizing, current AI could be categorized into two fields: data science and robotics.

AI should not be based on human cognition only, but on other forms of intelligence when it makes sense to do so. Look at a flock of birds. Isn't it smart? Thousands of birds flying close to each other typically create majestic patterns. This is natural collective intelligence. In addition, look at the rise and fall of species in evolution. Look at interactions of people and groups in a community. Interactions in social groups, teams, communities and organizations have their own intelligence that is interesting to be modeled and further understood. This is the reason why it is very important to have a good sense of systems whether they are natural or artificial. This paper tries to open a new way of considering systems for human systems integration (HSI), by considering **not only human cognition but more generally natural life mixed with artificial life**, which ends up in harmonious and symbiotic socio-technical systems.

At this point, it is important to clarify terms used in AI and Systems Engineering (SE), especially terms such as "agent" and "system," which have very similar meanings. The term "agent" is used in AI almost in the same way as the term "system" is used in SE. In AI, "an agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators." [16]. A system is a **representation** of: (1) a human or more generally a natural entity (e.g., a

[2] Association for the Advancement of Artificial Intelligence.

[3] https://aaai.org/Conferences/AAAI-20/aaai20call/

bird, a vegetal); (2) an organization or a social group (e.g., a team, a community); or (3) a machine or a technological entity (e.g., a car, a motorway) [2].

Distributed AI (i.e., multi-agent approaches) and system science have a lot in common. AI scientist Marvin Minsky defined an agent as an agency of agents [13]. Multi-agent systems can then be an alternative way of talking about systems of systems, defined in system science as a set of interconnected and interacting components. This is the reason why interdisciplinarity should be promoted (i.e., we should combine AI and SE, and more specifically HSI).

Expertise and experience have been extensively studied during the late 1980s and 1990s, especially in the field of knowledge acquisition for Knowledge-Based Systems (KBSs) [8]. KBSs are also known as expert systems or rule-based systems. This field of investigation supported some kinds of automation of expertise and experience. Unfortunately, it declined over the years since the mid-1990s, because it was not mature in terms of flexibility and support to creativity in provided services (i.e., in most cases, people were outperforming KBSs because of their flexibility to solve problems).

For example, we used KBSs to support experience feedback management in order to preserve and reuse experience and expertise knowledge. Large knowledge bases were developed, but were seldom used. Today, using digital twins (i.e., digital models and simulations of real-world systems), we can incrementally integrate experience feedback knowledge in a meaningful and usable way, using supervised machine learning. More specifically, we foresee digital twins as operations support for situation awareness, decision making and action taking.

2 Technology, organization and people: a systemic approach

The concept of system has been already introduced as a representation of humans or machines. It should be extended to organizations of humans and machines (i.e., a system of systems as a recursive definition of a system). A system has structures and functions that can be physical and/or cognitive. Fig. 1 presents a synthetic view of what a system is about.

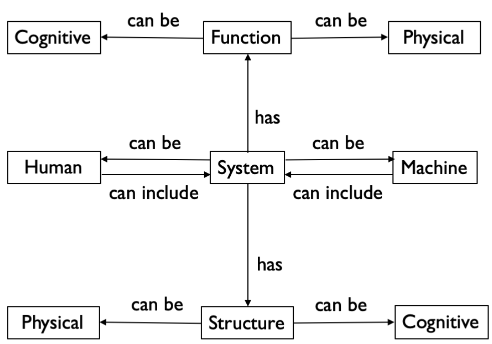

Fig. 1. Synthetic view of the system representation [2].

For a long time, engineers used to think about a system as an isolated system, or a quasi-isolated system, which has an input and produces an output. As for an agent in AI, which has sensors and actuators, a system has sensors to acquire an input and actuators to produce an output.

Each system should be interconnected to other systems either statically (in terms of system's structure of structures) and/or dynamically (in terms of time, system's function of functions, and their allocation). A system is a combination of technology, organization and people, which leads to the TOP model (Fig. 2), already developed in HCD [4]. Summarizing, a system, as a system of systems, should be represented by a network of systems where a network of functions could be dynamically allocated onto a structure of structures.

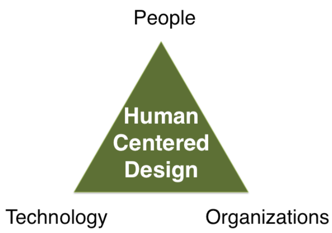

Fig. 2. The TOP Model.

3 Function allocation: looking for flexibility

From a general standpoint, function allocation among humans and machines can be handled using three design processes that can be associated to three operations processes (Table 1).

Table 1. Design and operations processes for human-machine function allocation.

Design process	Operations process
Substitution	Automation
Amplification	Interaction
Speculation	Augmentation

- **substitution** that consists in replacing human functions by machine functions and, in some cases, vice-versa with respect to context (e.g., in abnormal and emergency situations);
- **amplification** that consists in amplifying human functions using specific machine functions, and vice-versa interpreting machine functions' activity to enable people to keep appropriate situation awareness;
- **speculation** that consists in inventing machine functions that enable people to do what they are capable of doing, and discovering emerging human functions that are mandatory to deal with highly automated and autonomous systems.

Autopilots are substitution functions (e.g., they are able to follow a heading, a speed, and altitude and so on). Pilots can perform these functions "manually". Rigid automation takes care of these kinds of functions in pre-determined contexts. Therefore, substitution is directly associated with **automation** at operations time.

Context-aware search algorithms have amplification functions, which enable to find appropriate information by typing a few keywords in context, where context is incrementally learned by the machine from previous interactions for example [6]. These functions amplify human memory capacity since they do not only consider individual interactions, but also interactions from other people, "who are like you." Therefore, amplification is directly associated with **interaction** at operations time.

Compared to birds, people are handicapped; they cannot fly! Engineers speculated aircraft functions that enable people to fly. These functions are based on physical phenomena, such as thrust and lift (Fig. 3), that were modeled in the form of mathematical equations, which in turn were used to design appropriate machine structures and functions. Aircraft are prostheses that enable people to fly. In this sense, aircraft augment people capabilities. Therefore, speculation is directly associated with **augmentation** at operations time.

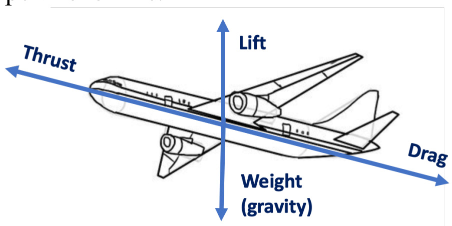

Fig. 3. Four forces of flight (thrust opposed to drag, and lift opposed to weight).

It is interesting to better understand the evolution from HFE to HCI to HSI communities in the light of the triptych (automation, interaction, augmentation). HFE was born from problems that needed to be solved in industry after World War 2, where machines were essentially mechanical and incrementally automated. Automation became a real issue because people had to adapt to it. The substitution of a human function by a machine function created the emergence of new human functions that were not necessarily anticipated by engineers. HFE specialists had to help fixing these issues. As a consequence, automation turned out to introduce rigidity when things started to go wrong.

In the beginning of the 1980s, computers started to be extensively used and created new issues related to HCI. A new community was created to study these issues. People were able to do more things using computers because software amplified their capabilities. However, these new machine functions did not remove rigidity in operations. Indeed, machine functions, even if they were highly interactive, were designed in specific contexts. Outside of these contexts, these functions are not operative and may lead to major problems.

Aircraft are good examples of augmentation of people's capabilities. However, solutions that have been found so far, such as on fixed wing aircraft, provide rigidity compared to what a flock of birds can do. Birds are far more autonomous and flexible that aircraft. Consequently, a new round of speculation should be carried out! More specifically, we should move from traditional single-agent-to-single-agent interaction to multi-agent function allocation.

4 From rigid automation to flexible autonomy

Control and management of life-critical systems is typically supported by operations procedures and automation. Automation is usually thought as automation of machine functions. Analogously, operation procedures can be thought as automation of people [3]. Problems come when unexpected situations occur, and rigid assistance (i.e., procedures and automation) may not work any longer, because system's activity is out of its validity context. **Problem solving** is at stake, and more specifically human problem solving. Instead of following procedures and monitoring automation, people need autonomy, first for themselves (i.e., human autonomy) and from machines (i.e., machine autonomy). We then deal with a multi-agent system, where agents incrementally become more autonomous through learning, and therefore should be coordinated. Fig. 4 presents these three options, which lead to the difficult problem of **function allocation**. Solving a problem requires enough technological, organizational and/or human flexibility (i.e., the TOP model is back again!).

Function allocation cannot be thought as a static a priori process. It is highly dynamic and systems should be flexible enough to be able to be modified incrementally. Flexibility has to be found along with the TOP model.

On the technology side, machines should be flexible enough to be modified if required. HSI requires integration of experience and expertise, which is often available in the form of cases solved in the past and potentially reusable in similar situations. AI extensively developed knowledge-based systems and case-based reasoning, which can be very effective when associated with supervised machine learning. Handling cases requires appropriate situation awareness, and therefore AI can supply approaches such as intelligent visualization, which involves deep learning. **Case-based reasoning** [1] is very useful in the context of experience feedback management. Case-based reasoning (CBR)[4] is based on four main processes: retrieval of one (or several) similar case(s) similar to a current case; reuse of previously used cases to elaborate a working-in-progress solution; revision of the working-in-progress solution by modifying its structures and functions until a satisfactory solution is found; recording of the successful solution for later reuse. CBR should be develop within a statistical framework in order to perform probabilistic inference as opposed to deterministic inference [18].

[4] Case-based reasoning is rooted in Roger Schank's research work on human dynamic memory (Schank, 1982).

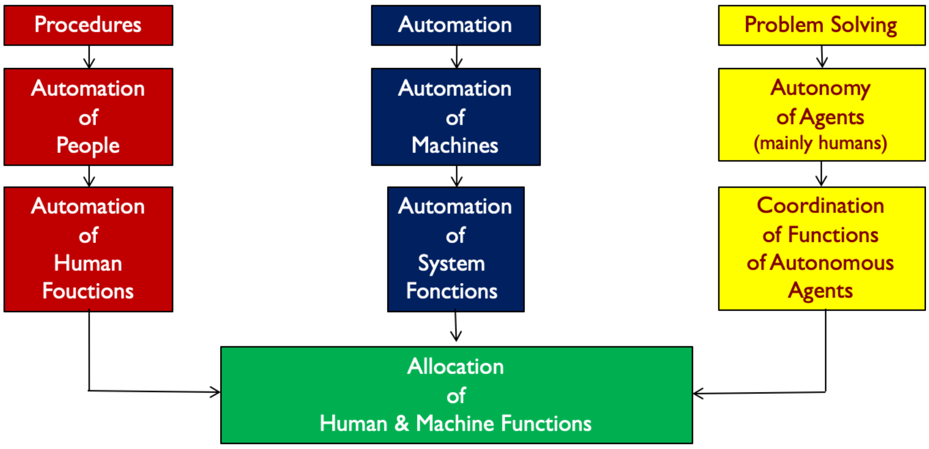

Fig. 4. Four forces of flight (thrust opposed to drag, and lift opposed to weight).

Machine Learning (ML) and even more importantly **Deep Learning** (DL) have become very dominant during the last few years. Obviously, ML can be very interesting within our flexible autonomy endeavor. Indeed, flexible autonomy should be based on experience, which is acquired incrementally through a large number of try-and-error activities. As a matter of fact, positive experience is as important as negative experience. If incidents and accidents are very well documented and can serve as useful data for learning, we should focus even more on positive experience (i.e., things that went well). ML algorithms are developed to make sense of large amounts of data (i.e., the now famous "big data"). They enable the elicitation of patterns, information organization, anomalies and relationships detection, as well as projections making. These algorithms will enable fine tuning the way increasingly-autonomous systems will perform more safely, efficiently and comfortably. They can contribute to improve task execution precision. DL enables the management of higher abstraction levels than ML (e.g., image and speech recognition). DL is based on many kinds of multilayer neural network technology. It enables content generation and improve existing contents, such as automated coloring of black and white images for example.

Intelligent visualization [9,11,17] is a growing field of investigation that attempts to develop visualization methods and tools that enable complex data to be better understood by people. In other words, it helps people to be more familiar with complex systems when they are appropriately visualized. Remember the adage, "A picture is worth a thousand words." In addition to static pictures, dynamic animations, simulations and movies can be displayed to improve understanding of complex data and concepts. AI can support intelligent visualization as recent developments show in visual analytics [10]. More specifically, it is highly suggested that human visual exploration should be mixed with data mining for the creation or management of existing knowledge, which in turn can be used to select the right data (Fig. 5).

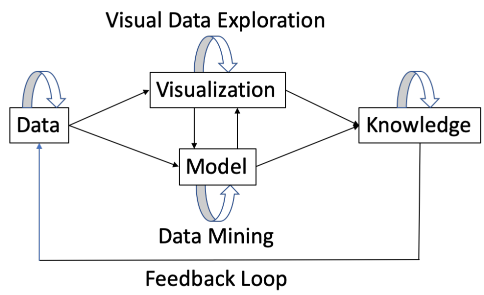

Fig. 5. Human (visual) and machine data analysis (HSI) – adapted from Keim et al. [10].

On the organizational side, it should be easy to switch from supervision to mediation to cooperation, and vice versa all the way. Indeed, there are three main **systemic interaction models** presented on Fig. 6 [2].

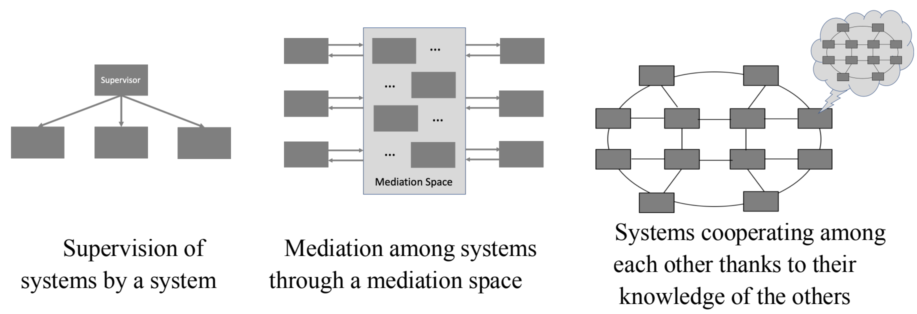

Fig. 6. Three systemic interaction models of multi-agent systems.

- **Supervision** is when a system (i.e., a supervisor) supervises interactions among other systems that interact among each other. Supervision is about coordination. This interaction model is used when systems do not know each other or do not have enough resources to properly interact among each other toward a satisfactory performance of their constituting system of systems.
- **Mediation** is when systems are able to interact among each other through a mediation space composed of a set of mediating systems, such as ambassadors and diplomats. This interaction model is used when systems barely know each other, but easily understand how to use the mediation space.
- **Cooperation** is when systems are able to have a socio-cognitive model of the system of systems which they are part of. Each system uses its socio-cognitive model of its environment to interact with the other systems to maximize some kinds of performance metrics. Note that this principle is collective and democratic. Other principles could be used such as dominance of a system over the other systems (i.e., a dictatorial principle). This interaction model is used when systems know each other through their own socio-cognitive model, which is able to adapt through learning from positive and negative interactions.

On the human side, people can be designers, engineers, developers, certifiers, maintainers, operators or end-users, trainers and dismantlers (not an exhaustive list). People, in the TOP model, have activities and jobs. Anytime technology and/or organization change, people may change their activities and/or jobs. Sometimes, new technology may lead to people losing their jobs, or conversely new jobs (i.e., functions) should be created and therefore a new set of people might be hired (i.e., a new structure should be created within the organization). People have their own human factors issues, such as fatigue, workload, physical and cognitive limitations, and creativity [2].

System-of-systems infrastructure can be hierarchical or heterarchical for example. Evolution of digital organizations drastically changed people's jobs going **from old army hierarchical to heterarchical orchestra structures and functions** (Boy, 2013), with musicians, some of them being conductors and compositors. More formally, playing a symphony (i.e., a product), the orchestra organization requires five kinds of components:

1. music theory that is the common language (i.e., a framework and language for collaborative work);
2. scores produced and coordinated by composers (i.e., coordinated tasks to be executed);
3. workflow coordinated by a conductor (i.e., system of systems activity);
4. musicians performing the actual symphony (i.e., the actual system of systems);
5. audience listening produced symphony (i.e., end users of the product).

Fig. 7 presents a workflow that integrates these AI techniques from the real world to databases and back to the real world, using a digital twin. Note that we deliberately choose a multi-agent framework that is well suited for carrying out function allocation.

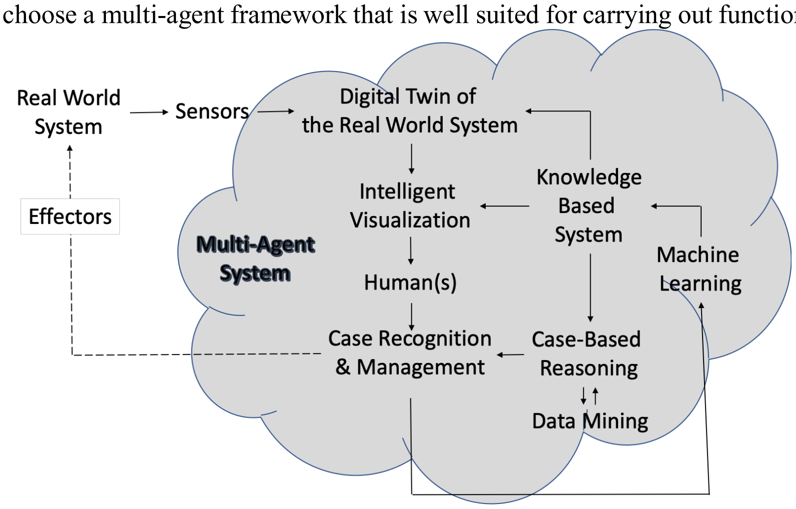

Fig. 7. Information workflow integrating AI techniques for various types of processing, such as experience feedback management and integration, decision making, diagnostic and repair.

5 Conclusion

This paper was produced to support the **first workshop on the application of Artificial Intelligence for Systems Engineering (AI4SE 2019)**, and encourage research and innovation that mixes HSI and AI toward more flexible technology.

Flexible autonomy is mostly needed in abnormal and emergency situations, that is in problem-solving where people have to speculate appropriate solutions. This is precisely where AI could be efficient and effective by supplying tools that augment people's capabilities in problem solving.

Automation (software) should be reliable at any time in order to support safe, efficient and comfortable work. There are many ways to test software reliability [12,15]. However, what is most important is HSI reliability. We know that there is a **co-adaptation of people and machines** (via designers and engineers, as well as trainers and accumulated experience). This makes even more important to understand when machine become "intelligent" in the AI sense.

Human operators may accept some unreliable situations where the machine fails as long as safety, efficiency and comfort costs are not too high (i.e., acceptable degraded modes of operations). However, when these costs become too high for them, the machine is just rejected. This states the problem of product **maturity** [5]; the conventional capacity maturity model (CMMi) for software development [14], systematically used in most industries, does not guarantee product maturity, but manufacturing process maturity. Product maturity requires continuous investment of end-users in design and development processes. At the very beginning, they must be involved with domain specialists to set up high-level requirements right; this is an important role of participatory design. During the design and development phase, formative evaluations should be performed involving appropriate potential end-users in order to incrementally "invent" and discover the most appropriate future use of the product in an agile way.

Along these lines, human-systems integration and artificial intelligence should be cross-fertilized for the design of more flexible TOP-centered systems. This is a contributing account to the FlexTech approach currently developed at CentraleSupélec and ESTIA Institute of Technology.

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