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NEURAL NETWORK-BASED FRAMEWORK FOR INTELLIGENT SYSTEMS DESIGN IN THE CONTEXT OF A FOR-PROFIT ORGANIZATION

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Abstract

The development of Industry 4.0 centers around ‘Internet-of-Things’ -integration, seamless big data exploitation and the application of artificial intelligence. With these attributes, the aim is to create intelligent system-based smart environments, that are believed to bring along new and sustainable value creation opportunities. Adopting this development direction is essential for for-profit organizations from both a competitive and environmentally sustainable perspectives. However, the transition phase that is still going on in Industry 4.0’s development has brought up problems that need new and innovative approaches to be resolved.

The objective of this study was to examine, whether the concept of artificial intelligence could be extended to cover the physical layer of intelligent systems with a similar imitation process, that is behind computation mimicking human cognitive processes. During the biomimetic design process, analogical similarity between human nervous system and the technological development of Industry 4.0 was identified. The basic structures and mechanisms of human nervous system were abstracted into principles, and further concretized as a technical solution. The study resulted a framework proposing neural network analogy-based information system architecture, that unifies together the key concepts in Industry 4.0’s development and offers a new approach for intelligent systems design for for-profit organizations.

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Tiivistelmä

Industry 4.0 -aikakauden kehitys keskittyy 'Internet of Things' -ideologiaan perustuvaan integraatioon, big datan saumattomaan hyödyntämiseen ja tekoälyteknologian soveltamiseen. Näiden ominaisuuksien avulla pyritään rakentamaan älykkäisiin järjestelmiin perustuvia ympäristöjä, joiden uskotaan tuovan mukanaan uusia, kestävää kehitystä edistäviä arvonluontimahdollisuuksia. Voittoa tuottaville organisaatioille kehityssuunnan omaksuminen on yhtäältä kilpailukyvyn ja toisaalta ympäristön kestävyyden kannalta tärkeä tekijä. Kehitys on kuitenkin yhä murrosvaiheessa, jonka myötä esiin on noussut haasteita, joiden ratkaisemiseksi kaivataan uusia ja innovatiivisia lähestymistapoja.

Tämän tutkielman tavoitteena oli selvittää, voiko tekoälykonseptin laajentaa älykkäiden järjestelmien fyysiseen suunnitteluun samankaltaisella imitaatioprosessilla, joka luo pohjan ihmisen kognitiivisia prosesseja imitoivalle tekoälylaskennalle. Biomimetiikkaan pohjautuvan suunnitteluprosessin aikana ihmisen hermojärjestelmän ja Industry 4.0:n liittyvän teknologisen kehityssuunnan välillä tunnistettiin analoginen samankaltaisuus. Ihmisen hermojärjestelmään kuuluvia perusrakenteita ja -mekanismeja abstrahoitiin ensin käsitteiksi, jotka edelleen konkretisoitiin tekniseksi ratkaisuksi. Lopputuloksena syntyi viitekehys neuroverkkoanalogiaan pohjautuvasta tietojärjestelmäarkkitehtuurista, joka sitoo keskeiset Industry 4.0:n kehityksessä nousevat käsitteet yhteen ja tarjoaa uudenlaisen lähestymistavan älykkäiden järjestelmien suunnitteluun voittoa tuottaville organisaatioille.

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When the idea of this thesis first began to emerge on my mind, I could never have guessed what kind of journey I was going to have ahead while progressing it from a scratch to a (somewhat) complete piece of work. Coupled with a personal process of growth and recovery, it was a discourse between frustrating feelings of being ultimately stuck and sudden aha-moments that kept pushing me forward until the very end. A challenging but rewarding journey I learnt a lot from and, although learning may never stop, finishing this thesis was still a remarkable turning point in my life.

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Jennika Tukiainen

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1. INTRODUCTION

We are living in the age of fourth industrial revolution, Industry 4.0, that is fundamentally changing the world (Griffiths & Ooi, 2018; 29; Raptis, Passarella & Conti, 2019, 97052). The ongoing industrial transformation roots back to the birth of Internet and the previous revolutionary era of digitalization. Internet has now gone through four phases of evolution: from 1989's original 'read-only' form (Web 1.0) and, through the 'read-write' (Web 2.0.) and 'executable' (Web 3.0) forms, it has taken its current form of Web 4.0, a platform of multi-layer interaction (Choudbury, 2014, 8096-8900). In Industry 4.0, Internet is expanding everywhere, aiming to connect not only computers but a variety of technologies and other entities such as people and processes (Khan, Wu, Xu & Dou, 2017, 3; Colakovic & Hadzialik, 2018, 18; Gold, Kenneth, Wahlstedt & Sachs, 2019, 23) as a comprehensive network, conceptualized as Internet-of-Things (Atzori, Iera & Morabito, 2010, 2787; Lasi, Kemper, Fettke, Feld & Thomas, 2014, 239). The visioned IoT-network is integrative in horizontal, vertical and end-to-end dimensions (Stock & Seliger, 2016, 536), creating an interconnected Cyber-Physical Systems (CPS) that embeds the actors and processes of both physical and digital worlds together (Lu, 2017, 4; Milenkovic, 2020, 1).

A key element in the development of Industry 4.0 is big data, described as another integrative component in Industry 4.0's envisioned network model (Khan et al. 2017, 1-3). The idea of the IoT-based network is to enable a seamless data flow, for information to be available at the right time at the right place (Stock, Obenaus, Kunz & Kohl, 2018, 256). Digitalization and the evolution of Internet shifted a great part of our daily human-to-human interaction and other activities online. As a result, the generation of data exploded, transforming 'just data' into what is called now big data (Raptis et al., 2019, 97054). Big data's distinctive characteristics in comparison with traditional data are often described with aide-mémoire V, that were originally three V's for volume, velocity and variety (Laney, 2001), but over time has been complemented with additional V-attributes such as valence, veracity, variability and value (Saggi & Jain, 2018, 763-764). The discovery and exploitation of big data has revealed its significant potential (Fan, Han & Liu, 2014; Jagadish, Gehrke, Labrinidis, Papakonstantinou, Patel, Ramakrishnan & Shahabi, 2014), leading to the perception of its transformative effect to all the aspects of our lives (Cukier & Mayer-Schöenberger, 2013; Jagadish et al. 2014).

Another driver of the development in Industry 4.0 is Artificial Intelligence (AI) -based applications (Dastbaz, 2019, 7). The field of AI is described as a study of intelligent agents (Helmold, 2019,162) and has produced such technologies as Machine Learning (ML) algorithms that are capable of tackle complex problems and react to environmental changes (Rebala, Ravi & Churiwala, 2019, 5). This type of intelligent technology is assumed to give advanced characteristics for the Industry 4.0's systems (Colakovic et al. 2018, 19, 31). 'Intelligent' or, equivalently, 'smart' seems to be a quality overall desired with Industry 4.0's development, as it frequently appears in the related discussion through many concepts like smart environments, cities, factories and devices (Gandomi et al. 2015, 138; Garcia, 2019, Raptis et al., 2019, 97052; 33; Kumar, 2020, 12), intelligent systems and network structures (Stock et al. 2016, 537; Curry, 2020, 5), intelligent analytics (Peres et al. 2018, 138-146) and intelligent services (Colakovic et al. 2018, 19).

Industry 4.0's visioned smart environments (Garcia, 2019, 33) bring along new value creation opportunities with overall process optimization (Peres et al., 2018, 139; Garcia, 2019, 33). Altogether, the development of Industry 4.0 is believed to be transformative, influencing our everyday lives, economics, science and politics (Jagadish et al. 2014, 86; Jin et al. 2015, 59). However, the development is still in transition, which has resulted to challenges needed to overcome to fully realize the value creation opportunities. For instance, it is still needed to address the effective way for establishing IoT-connections (Stock et al., 2016, 537) and, to close the gap between envisioned and practical sides of big data (Ekbia et al., 2015, 1538). Big data has no generally accepted definition (Gandomi & Haider, 2015, 138) and its different essence in comparison with traditional data, for which most data management methods and tools have been designed, has led to significant incompatibility issues (Jin, Wah, Chen & Wang, 2015, 62-63; Sivarjah et al. 2017).

Instead of value creation, coping with the transition challenges of Industry 4.0 may negatively impact on profit-organizations' business performance. Adaptation to the transformation is essential for for-profit organizations to maintain or fortify their competition position (Kotler, Berger & Bickhoff, 2010, 12, 44). Quick adoption of Industry 4.0's key development trends such as strategic big data management may provide competitive advantage (Cavanillas, Curry & Wolfgang, 2016). As well, there is a wider importance for for-profit organizations to adopt the changes, as Industry 4.0 is expected to enhance sustainable development (Stock et al. 2016, 539). Economic exchange and the existence of for-profit organizations is rooted to *homo economicus* paradigm (Hlaváček, Hlaváček, Pelikán, Žák & Havlíček, 2013, 14). The logic behind the paradigm is based on the assumption of humans being purely rational and choosing a strategy that maximizes their personal profit and, is believed to be a significant reason for the current unsustainable state of our planet (Ferraro & Reid, 2013, 127).

How for-profit organizations should approach the development of Industry 4.0 to speed up their adaptation process in order to create more value but at the same time improve the sustainable performance? Traditionally viewed, these goals are contradictory with each other (Levine, Chan & Satterfield, 2015, 22). Industry 4.0, however, is dismantling our existing systems and replacing them with novel and innovative solutions with a rapid pace (Griffiths et al., 2018. 29). The course seems right, as saving our sensitive environment that is currently overburdened due to human presence requires a fundamental change in our mindsets and not only polishing our economic, politic and overall operation (Cochrane, 2019, 13-14). Likewise, the ongoing coronavirus pandemic has concretely revealed that, the sustainability issue does not concern only the environment but as well, the humanity itself. The pandemics' pervasive negative effects have exposed the vulnerability underlying behind our current ways to think, act, design and construct (Nicola et al. 2020, 185-190).

Intelligence is a general quality that is desired to be added to the environments and systems in Industry 4.0 to give them advanced characteristics such as the capability to predict and accurate reactivity to the changing environment. The study of AI is based on mimicry of higher human cognitive functions (Helmold, 2019, 162) and AI

-based intelligent computation methods are perceived as a core element of intelligent system design (Prudencio & Lurdemir, 2015, 1; Nichols & Newsome, 1999, 35). More advanced mimicry of higher cognitive function is required to produce systems that promote the desired advanced qualities (Kujala & Saariluoma, 2018, 8). However, if the purpose is to establish environments and systems that are holistically intelligent, should intelligence not be examined and mimicked with a wider scope than just a mimicry of cognitive functions? Howard, Eiben, Kennedy, Mouret, Valencia and Winkler (2019, 12) argue for it, pointing out that intelligence results from a sum that includes the body and the environment of an intelligent agent, together with the brain and its cognitive processes.

A specific study field called biomimetics is based on the similar imitation of biological systems than the study of AI's mimicry of higher cognitive functions. In biomimetics, natural structures, mechanisms and processes are systematically examined and mimicked to transfer their principles into artificial design for the purposes of optimization and problems solving (Vincent, Bogatyreva, Bogatyrev, Bowyer & Pahl. 2006, 471-472; Cohen & Reich, 2016, 3). Biomimetics has produced many design solutions, including some in which the target of the improvement has been a physical structure (Fish, Weber, Murray & Howle, 2011; Hwang, Jeong, Min Park, Hong Lee, Wook Hong & Choi, 2015). Similarly, approaching intelligent systems design for for-profit organizations with biomimetics could lead to a solution, in where mimicking intelligence covers more than computational layer of the system. The premise of biomimetics lies on evolution (Fisch, 2017, 797), that can be described as a natural mechanism driving the adaptation of living organisms in constantly changing environment (Fogel, 2000, 26). Evolutive iteration between mutation and selection acts as a natural force of optimization and, the centuries long iteration process has resulted solutions that are inherently effective and sustainable. Overall, natural systems and their functionality is described to be evolved to achieve maximum performance with minimum amount of resources (Bhushan, 2009). This same idea is for what all the for-profit business is based on.

The objective of this study is to attempt to complement computational AI of intelligent systems of for-profit organizations by extending the mimicry of intelligence to a physical layer of the system. The objective is to address, whether mimicking natural intelligence more comprehensively and not just on the level of computation could add more intelligence to for-profit organizations' information systems and, thus, give to it characteristics that improve the survival in competition as well as concerns sustainability. The systems improvement is approached with biomimetic design.

1.1. The structure of the study

The study is structured as follows. The following sub-sections of part 1 describe the research setting of this study by introducing research problems, research questions and delimitations, explaining the methodology used and presenting the key concepts and theoretical framework of the study. The development of Industry 4.0, approached with the concepts of intelligence and value creation, is reviewed in part 2. Part 3 focuses on design by examining what is needed to take into consideration in organizational design in the era of Industry 4.0 and examines suitable approaches. Part 4 is centered on design likewise, by introducing biomimetics as a study field and previous work related to the mimicry of natural intelligence. Parts 5 and 6 present the methodology used, and the design process of this study. Final part 7 discusses about the results, their practical and theoretical implications as well as the limitations of the study and, presents some suggestions for future research.

1.2. Research problems, research questions and delimitations

One the one hand, the vision driving Industry 4.0 is expected to have a fundamental influence on our lives and reshaping everything, including our mindsets (Cukier et al. 2013; 39; Jagadish et al. 2014, 86; Jin et al. 2015, 59). Industry 4.0 is progressing rapidly and fundamentally re-organizing our systems (Griffiths et al. 2018. 29). On the other hand, the change in mindsets and innovativeness is perceived as a need to keep the transformation going forward for instance to respond accurately to the sustainability problems (Cochrane et al. 2019). This study attempts to examine the underlying problems and drawing from that, find new ways to approach the issues that are on the way to turn the vision of Industry 4.0 into reality.

Intelligence seems to be a desired quality and in the vision of Industry 4.0, and it is assumed to manifest itself in ways that brings advancement such as predictability, environmental reactivity and complex problem solving. The concept of AI, however, seems to be centered around computation, although desired intelligence is more comprehensive. For achieving more comprehensive intelligence, this study attempts to extend the concept of AI beyond computation to consider the physical level of visioned cyber-physical systems as well. The goal is to design a cyber-physical system, in where the intelligence is present both in digital and physical layers. The design process is approached with biomimetics that follows similar path than the mimicry in computational AI.

The design context of this study is limited to the context of a single for-profit organization. A for-profit organization was selected as a design target as their need to adapt on environment is important internal and external levels of sustainability. As for-profit organizations are economic entities, their position in a competitive market environment determines their success and, reacting to the environmental changes is essential for responding the behavior of the competitors (Kotler et al., 2010, 12). As well, the very essence of for-profit organizations is grounded on the paradigm that is contradictory with sustainable development (Hlaváček et al., 2013, 14; Ferraro & Reid, 2013, 127) which is problematic considering the state of the environment (Cochrane, 2019, 13-14). Industry 4.0 is believed to be a paradigm that leads to more sustainable value creation (Stock et al. 2016, 539), which makes the adaptation of the for-profit organizations important also from environmental perspective. Based on the problems presented, the main research question (RQ1) of this study is as follows:

RQ1: How to design an intelligent cyber-physical system for a for-profit organization?

As intelligence seems to be generally desired quality in the development of Industry 4.0 and, the goal is to extend artificial intelligence to cover more than computational processes, it is needed to define the attributes that are assumed to enable the desired intelligence. Sub-research question RQ2 was set to guide this investigation:

RQ2: What are the intelligence attributes of a cyber-physical system?

The study is limited to the context, in which the target scope for the design is a single for-profit organization. The design process is based on biomimetics, but, to address, what is needed to consider specifically with the design target, the sub-research question RQ3 of this study is the following:

RQ3: What to consider in organizational design?

1.3. Research methodology

This study adopts a design research approach. Design research is grounded on scientific design that fuses the elements of a research and a design process by being based on scientific knowledge and mixing both intuitive and non-intuitive design methods (Cross, 1993, 19). Design sciences, such as the study of AI, can be distinguished from purely analytical sciences: they aim to examine the behavior of designed artifacts under different conditions (Collins, Joseph & Bielaczyz, 2004, 17). The 'design methods movement' emerged after it was noted, that certain design in such fields as architectural, engineering, material and behavioral sciences have strong foundations in science and, that intuitive design methods are not sufficient for modern complex industrial design (Cross,1993, 19). The complexity of industrial design has only increased over time and, will assumably keep increasing as the development of Industry 4.0 forwards, which makes the approach ideal for the study. Edelson (2002, 118) states, that if the theory behind the design is incompletely specified, it is unable to meet the practical demands and needs of designers. The study attempts to help in closing the gap between the theory and design of Industry 4.0's intelligent systems design.

As it is attempted to follow a similar path with design as in current AI-study, that is, mimicking natural intelligence, the basis of the methodology of this is in biomimetics. The design adaptively follows biomimetics design process stages defined by Cohen et al. (2016, 21-25). The general steps of the process consist of problem definition, identifying a natural analogy source, solution abstraction, solution transfer and evaluation and iteration. Although the mimicry in AI is not typically counted in systematic biomimetic study it is based on similar process (McCulloch & Pitts,1943), in where the analogy of natural cognitive functions is attempted to be transferred into technical solutions. The study also adopts Socio-Technical Systems design approach, that considers the complex and systemic nature of the organizations and the interconnection social and technical layers within. The design process of this study is constructed by adapting and embedding the elements from both methods and process with the following steps: problem statement, solution abstraction, solution concretion and evaluation. Part 5 discusses about the methodology with further details.

1.4. Key concepts

The following list explains the key concepts of this study:

Industry 4.0 is the fourth industrial revolution after mechanical, electrical and information revolutions (Lasi et al. 2014, 239; Peres, Rocha, Leitao & Barata 2018, 138). The development of Industry 4.0 is focused on building smart environments with IoT-integration establishment, big data exploitation and AI-technology application (Stock et al. 2016; Azizi, 2019, 1; Curry, 2020, 5).

Integration refers to the development of vertically, horizontally and 'end-to-end' integrated network that is based on Internet-of-Things (IoT) ideology (Atzori et al. 2010, 2787; Stock et al., 2018, 256). The concept of IoT refers to tangible and intangible entities, such as machines, people and processes that are connected as a network through the Internet. IoT builds a bridge between physical and digital world, merging them into Cyber-Physical Systems (CPS).

Big data is a concept that distinguish post-digitalization and 'traditional' data. Digital transformation led to the evolution of data, giving it new characteristics in terms of the amount, form, behavior and quality (Laney, 2001; Saggi et al., 2018, 763-764; Raptis et al., 2019, 97054). No exact and generally accepted definition for big data exists (Gandomi et al. 2015, 138).

Artificial Intelligence (AI) refers to non-natural intelligence that typically imitates human cognitive processes, as well as, to a field of study that examines and develops intelligent agents. Intelligent agent refers to any device that is able to perceive the environment and react the way that leads to a maximized success for achieving the goals. (Helmold, 2019, 162)

Intelligent systems are systems with built-in intelligence, that gives them the capability to meaningfully acquire, reason and interpret data and present intelligent behavior such as learning, meaning extraction and strategy identification (Curry, 2020, 5). They combine elements of integration, big data exploitation and AI-technology application, attributes derived from the key concepts of Industry 4.0. Intelligent systems enable the establishment of smart environments and, with added intelligence they incorporate new sources for value creation. (Stock & Seliger, 2016, 537; Azizi, 2019, 1; Curry, 2020, 5).

Biomimetics refers to a systematic examination and mimicry of biological mechanisms, processes and structures in order to improve artificial design (Vincent et al. 2006, 471-472; Cohen et al. 2016, 3) Biomimetics is based on the analogical transfer and, its premise embraces the idea of biological systems being inherently efficient and sustainable due to evolutionary adaptation process of mutation-selection iteration (Fogel, 2000, 26; Fisch, 2017, 797).

Artificial Neural Networks (ANN) is a sub-class of AI-study. ANN-models are based on the connectionist approach of human cognition and neurobiology (Medler, 1998, 21; Huitt, 2003) and attempts to imitate neural information processing for the purposes of complex problem-solving and optimization. (Ding, Li, Su, Yu & Jin, 2013)

1.5. Theoretical framework

Figure 1 illustrates the theoretical framework of this study. Intelligence (or its equivalent smart) is a frequently appearing quality in literature, that discusses about the envisioned goals of Industry 4.0. Based on this, the key technology concepts, that arise as enablers of intelligence, were generalized into intelligence attributes. Specifically, the intelligence attributes serve as components of intelligent systems, that form a basis for smart environments with new value creation opportunities.

Only one of the identified intelligence attributes, that is, AI -applications, has a clear definition for how the intelligence is achieved: by mimicking higher human cognitive functions. The study examines, if a similar process of mimicry could result intelligence that is not only existent in computational level but covers the intelligent systems more comprehensively, both in physical and cyber-levels. Biomimetic design process is used to identify an intelligent system that has analogical similarity between the Industry 4.0’s visioned intelligent systems, to transfer its principles into a technical solution for the improvement of artificially intelligent systems design. The design context in this study is a for-profit organization as the adaptation to the changing environment in Industry 4.0 is important to their own survival as well as for the sustainability of the environment. Biomimetic design process is expected to lead to a solution, that is more intelligent, covers the visioned qualities and, thus, improves for-profit organizations' value creation as well as sustainable performance.

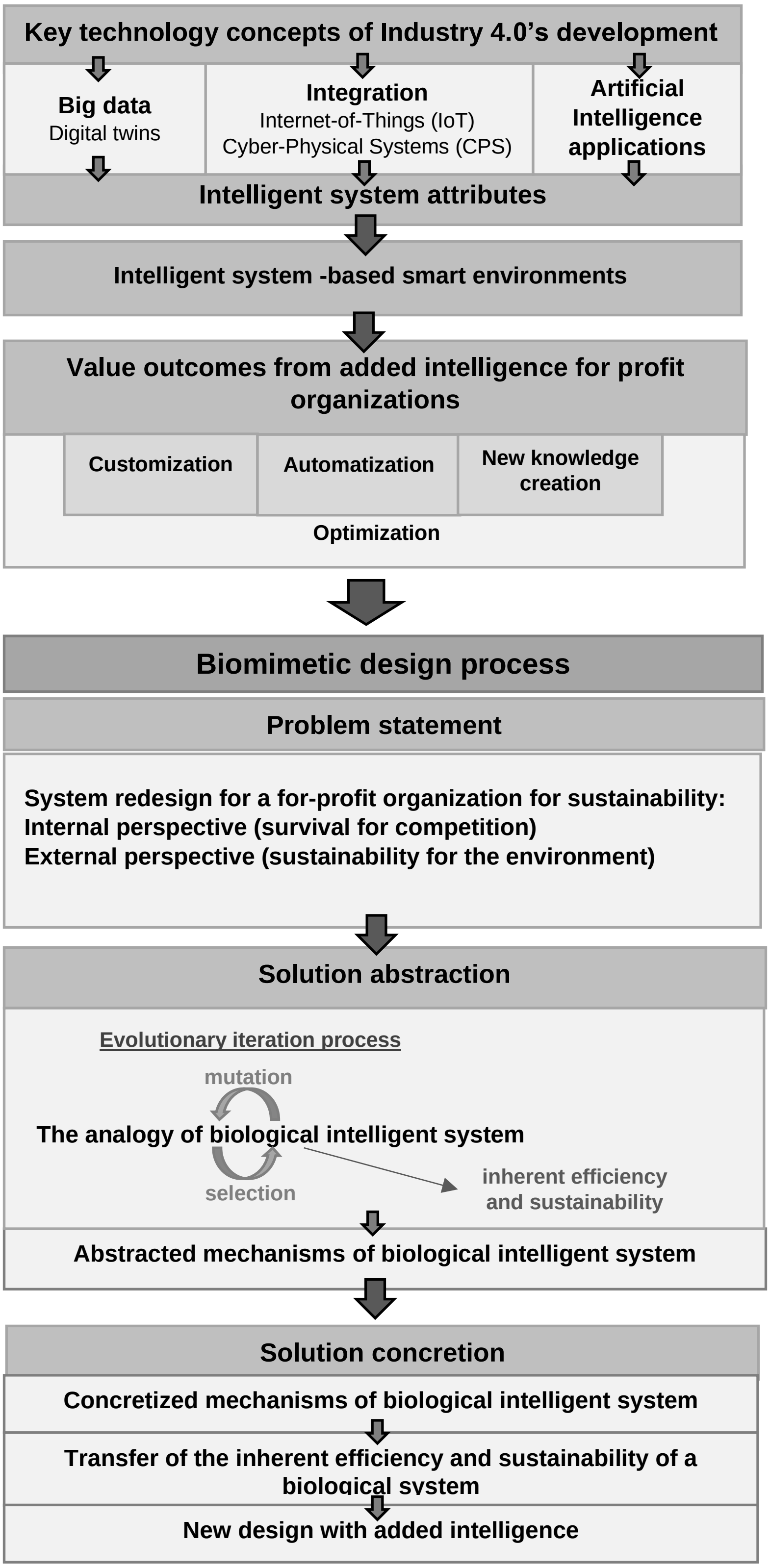

Figure 1: Theoretical framework of the study

2. INDUSTRY 4.0 – VALUE CREATION THROUGH ADDED INTELLIGENCE

Industry 4.0, also known as Industrial Internet, is a current ongoing paradigm shift following the previous mechanical, electrical and digital industrial revolutions (Lasi et al. 2014, 239; Peres, Rocha, Leitao & Barata 2018, 138). The development in Industry 4.0 is centered around the system integration based on the establishment of intelligent cross-links (Stock & Seliger, 2016, 537), information processing that combines big data and advanced information management methods (Curry, 2020, 5) and the development and application of Artificial Intelligence (AI) -based technology (Azizi, 2019, 1). The integrative network allows seamless data flow and combined with the exploitation of big data by using advanced methods, including AI -based solutions, the system model creates an environment with new opportunities for value creation.

'Intelligent' or its equivalent 'smart' are terms generally used to describe the development of Industry 4.0. Industry 4.0's smart environments refer to IoT-based sensor-actuator networks that enable uninterrupted information distribution (Garcia, 2019, 33; Gupta & Gupta, 2020, 7). Smart environments are based on intelligent systems, defined to comprehend built-in intelligence, that gives them the capability to meaningfully acquire, reason and interpret data and present intelligent behavior such as learning, meaning extraction and strategy identification (Curry, 2020, 5). This type of intelligent data analysis is real-time data exchange between heterogenous components of IoT-network, and it supports new knowledge creation (Peres et al. 2018, 138) Smart environments create conditions for smart factories to operate ways that improve manufacturing processes like allowing interoperability, bringing more convenience to maintenance and lowering costs (Raptis et al., 2019, 97052). As well, intelligence appears in device-level and covers advanced technology such as smartphones, smart glasses, sensing systems and robotics (Raptis et al., 2019, 97052)

2.1. The attributes of intelligence

Curry's (2020, 5) definition of the built-in intelligence in systems is enabled with the key technology initiatives in Industry 4.0. integration with IoT-connections, exploitation of big data and application of AI-based technology, which all of them are key characteristics driving Industry 4.0's vision. They are referred as intelligence attributes in this study. Added intelligence is achieved through the integration of different components, which gives self-organizing capabilities to regular machines and followingly, improves overall performance (Lee, Kao & Yang, 2014, 3). Big data is said to incorporate cognitive capabilities (Lugmayr et al., 2017, 198; Sivarjah et al., 2017, 1538) and AI -based technology is intelligent by definition.

2.1.1. IoT-integration

First intelligence attribute of Industry 4.0's intelligent systems is integration. Establishing fully integrated connectivity supports the evolution of industries and their critical activities, as well as their communication requirements (Gold et al. 2019, 43, 25). Internet of Things (IoT) is generally associated as one of the foundational concepts in Industry 4.0 (Milenkovic, 2020, 5). IoT refers to a network model, in which entities are interconnected through Internet enabling information to be exchanged and communicated seamlessly (Chen, Xu, Liu, Hu & Wang, 2014, 349). Using the term entity in the context of IoT-network is to describe how the concept aims to a holistic integration. Technology is one remarkable entity group in IoT-networks as Industry 4.0 is found to be an aggregation point for over 30 different fields of technology (Chiarello, Trivelli, Bonaccorsi & Fantoni, 2018, 244). In addition, with technology and machines, IoT connects other entities as well, both tangible and intangible. Examining the interconnectivity of IoT-ideology has generated sub-concepts for it, such as IoS for Services, IoP for People and IoE for Energy (Khan et al. 2017, 2; Lu, 2017, 2), specifying the entity type the network connects. Likewise, IoT-interconnection intertwines general level activities and processes such as identification, computation, sensing, and networking itself (Colakovik et al. 2018, 18).

Milenkovic (2020, 1) delineates that the IoT-development is building a bridge between a physical and digital world by adding a new dimension to the Internet, which improves its awareness of the real world. A specific term that has emerged to describe the fusion of digital and physical layers of reality is Cyber-Physical Systems (CPS) (Lu, 2017; Peres et al. 2018), another concept that regularly occurs in

Industry 4.0 related literature. CPS refers to systems with fundamentally intertwined physical and digital components (Zhou et al. 2015), built upon a core of computation and communication, from which the activity of the system is monitored, coordinated, controlled and integrated (Rajkumar et al. 2010, 631). Information quantified into data has an integrative role in CPS (Khan et al. 2017, 2) and is the digital element of CPS. Tangible entities of IoT are integrated with actuators, sensors and embedded software, that enable the data flow for processing and communication (Stock et al. 2018, 18). Lee, Kao and Bagheri (2015, 19) describe two main functional components of CPS being a connectivity that enables two-directional real-time data flow between data acquisition from physical layer and information feedback from digital layer. Digital layer that is constructed to enable intelligent data management, analytics and computational capability (Lee et al. 2015, 19).

The integration that is achieved by establishing IoT-connections occurs multi-level, in horizontal, vertical and end-to-end dimensions (Stock et al. 2016, 537; Peres et al. 2018, 138). Horizontal integration concerns the tangible entities of IoT that are present on the physical layer of CPS. It is enabled with interlinks between all the actors and objects of network, both in inter- and intraorganizational level. (Peres et al. 2018, 138). End-to-end integration refer to the intangible entity interconnection in digital layer. It is based on processing data and digitalizing all phases of product life cycle (Peres et al. 2018, 138). End-to-end integration aggregates processes and technologies such as Service-Products System (SSP), Cyber-Physical Production Systems (CCPS) information and communications technology (ICT), Enterprise Architecture (EA) and Enterprise Integration (EI) (Lee et al, 2014, 4; Lu, 2017). Vertical integration refers to the merge of cyber and physical layers. It creates internal integration and harmonizes two previously presented integrations (Peres et al. 2018, 138).

2.1.2. Big data

Data is a crucial, integrative component of the technology development in Industry 4.0 (Khan et al. 2017, 1-3). It is an enabler of the fusion of physical and digital world (Raptis et al., 2019, 97054). Over the last decade, big data has provoked cross-disciplinary discussion and debate among researchers and practitioners. The predictions of the emergence of big data has been speculated to origin from 1990's, but the term became popular in 2011 (Gandomi et al. 2015) and, ever since the interest in research of big data has grown in explosive rate (Akoka et al. 2017). The reason for the hype around big data is the discovery of its potential. It has been said revolutionize every aspect of our lives, business, science and government and affect to the ways how we live, work and even think (Cukier et al. 2013, 39; Jagadish et al. 2014) The use of big data has been associated with better innovation capabilities in companies in terms of propensity and intensity (Niebel et al. 2019). The utilization of big data has led to significant and discoveries in many fields such as in social sciences, finance, biomedicine and astronomy (Fan et al. 2014, 293Jagadish et al. 2014, 86). Data is stated as "a new oil", effective data management is perceived as key competitive advantage in business (Cavanillas, Curry & Wolfgang, 2016, 3), resulting the adaption of big data management into traditional and widely used business models such as Big Data SWOT-analysis (Ahmadi et al. 2016) and data value chain models (Miller, et al. 2013; Curry, Beckman, Munné, De Lama & Zillner, 2016; 18).

Despite of the vast amount of research concerning big data, there is still unclarity of what it exactly is and how it should precisely be defined. The evolution of the concept and its definition have been confusing and, research has shown big data is understood different way by different actors (Gandomi et al. 2015). The prefix 'big' emerged to distinguish big data from what data traditionally used to be. Fairly established way to describe distinctive characteristics that address the 'bigness' of this data is with V-characterization, that began from three V's for volume, variety and velocity after Laney (2001) but has been complemented with additional attributes such as valence, veracity, variability and value as it has been researched more (Saggi & Jain, 2018, 763-764).

The use of big data has shown significant potential to create value. However, there is still a gap between the practical reality of big data and the visions associated to it (Ekbia et al., 2015, 1538). Attempting to fit big data to the data processing and management systems and tools, that are designed for 'just data' has led to significant incompatibility problems. Jin, Wah, Cheng and Wang (2015, 62-63) describe the general issue of big data management as grown complexity occurring in the levels of computation, system and data itself. Sivarajah et al. (2017, 265) divide the challenges into data-, process- and management-related categories. Although the discussion concerning big data is often domain-specific, the issues seem to have similar underlying structure and synthesis (Ekbia et al., 2015).

More specific issues that are related big data management challenges can be identified by examining certain activities that are a part of data management process. Issues concerning data acquisition are, for example, identification of the proper data source, data quality control, unmet computation and memory requirements and data mining technique related problems (Braun, Kuljalin & DeShon, 2018). Problems that can arise in activities in data curation can concern the recoding multi-structural data into uniform and, finding a proper information process for it (Jagadish, et al. 2014). The issue is remarkable as, by estimations, 90 % big data is in unstructured form (Sivarajah, 2017, 263). Exploitation issues include computational cost and algorithmic instability (Fan, Han & Liu, 2014), and some related to the validity of the analysis such as spurious correlations, noise accumulation and incidental homogeneity (Sivarajah et al. 2017, 263). Big data visualization is problematic in terms of scalability with traditional tools that are not designed to present extremely large amounts of data and due to limited screen space (Agrawal et al, 2015), which, likewise, makes big data exploitation challenging.

The general classifications of big data management issues indicate the existence of multi-layer and multi-dimensional issues in attempts to manage big data and, the examination of more detailed literature confirms, that challenges in big data management may exist in every phase and activity of data management process. Girffiths et al. (2019, 29) suggest taking a different approach that begins from critical decisions needed and, through defining what kind of information is required to make these decisions, it would be determined what kind of data is required to obtain the information. As well, there has been critic that the big data discussion is too centered around the V-characterization. Lugmayr et al. (2017, 198) argues for the need for shifting the discussion from technical perspective towards more epistemological view of big data and, followingly, introduces the concept of cognitive big data with an emphasis of interdependency between computerized data processing systems and human mind. Likewise, Sivarajah et al. (2017, 263) bring up the cognitive essence of big data, defining it as an artefact of individual and collective human intelligence that is mainly generated and distributed through the technological environment.

The exploitation of big data has led to innovative findings in various use contexts, which is a clear proof of its potential as a source of value creation. However, big data seems to be overall incompatible with the traditional data management methods, there is no consensus about its definition and, the current approaches for its examination have already received critics. All of this indicates that a new way to approach big data needed. As Lugmayr et al. (2017, 198) and Sivarjah et al. (2017, 1538) have pointed out, big data has characteristics that can be defined as cognitive. In other words, big data can be argued to incorporate intelligence. Rapid digital development can be said to cause the evolution of data, from its traditional form to big data. As it differs greatly from pre-digitalization data, extracting the intelligence out from it requires as great shift in the approach of its management.

This observation shifts the discussion to digital twins. The fusion of physical and cyber reality has generated the concept of digital twin (Stock et al. 2018, 256). It refers to a digital counterpart of a physical object (Kaur, Mishra & Mahehswari, 2019, 5) and one of the objectives in Industry 4.0 is to create an abstraction layer in which these cyber entities represent the physical layer of CPS (Peres et al. 2018, 139). A digital shadow that formulates from the processing data of the objects, such as products or equipment in a physical layer of CPS is a base element of a digital twin (Stock et al. 2018, 256). The basic architecture of digital twin consists of technology for sensory and measurement activity, IoT-interlinking and machine learning elements (Kaur et al., 2019, 5). Chen et al. (2014, 177) state how IoT-paradigm leads to the embedment of large number of networking sensors into various devices in physical layer of CPS. They point out how big data generated by IoT differs from 'normal' big data and, how this IoT-based big data will become the central form of big data. The key technology in digital twins is the data and information fusion, facilitating the flow from raw sensory data to high-level understanding and insights (Kaur et al. 2019, 5). The concept of digital twin gives a framework for meaningful exploitation and approach for big data.

2.1.3. Artificial Intelligence applications

The development, research and application of AI-based technology is a central characteristic of Industry 4.0’s development (Shukla, 2018, 1-2). Artificial Intelligence (AI) is intelligence constructed by humans to machine in contrast natural intelligence that is existent in humans and other intelligent species by Helmold’s (2019, 162) definition. He describes the study of AI as a mimicry of higher cognitive functions, as well as study of intelligent agents that are devices capable to form a perception of the environment and act based on the drawn perception on the most optimal way. In past decades, the AI-technology development and the identification of potential new application areas have become more popular (Dastbaz, 2019, 7). The concept of intelligent systems originates from the field of Artficial Intelligence (Curry, 2020, 5).

A sub-field of AI called Machine Learning (ML) studies algorithms and techniques that generate automated solution for complex problems (Rebala et al., 2019, 5). ML can be divided into supervised and unsupervised learning (Alloghani, Al-Jumeily, Mustafina, Hussain & Aljaaf, 2020, 4). Machine learning provides several tools that are required for intelligent data analysis (Kononenko, 2001, 90) Intelligent machines are dependent on certain knowledge to sustain their functionalities and ML is able to create this type of knowledge: their techniques are based on learning and identifying patterns from data which can be used for the purposes to react to an environment (Alloghani et al. 2020, 4). Alloghani et al. (2020, 4).

2.2. The sources of new value creation

The central aim, synthetized by combining the central technology concepts arising in Industry 4.0 related literature, is to design and build intelligent systems. With a slight shift of perspective, Industry 4.0’s goal is to create intelligent environments (Garcia, 2019, 33). These environments are able to create value in terms of new knowledge generation, personification, automation and the overall process optimization through system intelligence enabled by the integration of entities and advanced data management (Peres et al. 2018, 138).

2.2.1. New knowledge creation

Industry 4.0’s visioned smart environments add value through the creation of new knowledge. Big data is rich and versatile in its nature, as addressed with its commonly used V-characterization. It conceals hidden insights that can be extracted with advanced data processing methods such as the ones that imitate higher human cognitive functions. The impact of big data analytics in terms of creating new knowledge is expected to be all-encompassing: big data has potential to bring transformative depth to the knowledge that concerns economics, science and politics with the consideration of sustainability aspects as well (Jagadish et al. 2014, 86; Jin et al. 2015, 59). The use of big data has been associated with better innovation capabilities in companies in terms of propensity and intensity (Niebel et al. 2019).

In addition, with the new knowledge gained with big data analytics, smart environments may serve as a base for new knowledge creation as such. IoT-network may shape knowledge management dynamics by adding new actors to the network and new knowledge can be gained from these actors (Bettiol et al. 2020, 7). As well smart environment and system development contributes new knowledge creation related to the functionality of the organizations. The implementation of Industry 4.0 technologies for intelligent environments and the resulting integration of big data and ERP-systems have potential to generate new knowledge about the processes and products and, thus, improve organizational learning (Bettiol, Di Maria & Micelli, 2020, 7).

2.2.2. Customization

Industry 4.0’s development is expected to lead to high-level customization. Big data exploitation predicts higher consumer orientation (Jin et al. 2015, 59), which along with the environmental changes such as market globalization and Industry 4.0’s development in general have pushed manufacturers to rethink their traditional production methods (Azizi, 2019, 1). Environmental changes have influenced to the expectations of the customers by increasing them, which has initiated a manufacturing service transformation in Industry 4.0 (Lee, Kao and Yang, 2014, 4).

The trend has led towards increasing individualization in goods and services (Lasi et al., 2014, 239). Lee et al. (2014) compares this customization development of Industry 4.0 to Vandermerve and Rada’s (1988) manufacturing servitization, that is a customer-focused concept for value creation by combining products, services, support and knowledge. The vision and expectation of Industry 4.0’s development is to shift from mass production to mass customization (Peres et al., 2018, 139; Gold et al.; 2019, 24).

Industry 4.0 will not only provide more customized products and services for consumers, but, likewise, the customization covers organizational processes. Well integrated CPS creates thorough knowledge thoroughly about of the physical system that is monitored (Lee et al. 2015, 20). The data is collected from manufacturing processes and digital twin abstraction layer formed to model the physical world (Chen et al., 2014, 177; Stock et al., 2018; Kaur et al., 2019, 5) which also may lead to organizational learning and the understanding and knowledge of specific needs of a specific organization (Bettiol et al., 2020, 7). This knowledge can be turned into customization of intra-organizational processes.

2.2.3. Automatization

Automatization creates value by improving the efficiency of manufacturing and other organizational processes and releasing social capital for other work. Shukla (2018, 2) describes Industry 4.0 as a revolution of industrial automatization. Eventual breakthrough, that leads to mass automatization is expected, which will lead to benefits gained from scale effects and increased effectiveness in resource use in organizational activity. Automatization in Industry 4.0 occurs two-directionally: automatized production, in which human labor is replaced with machines and semi-automatized distribution, in where the management of supply chains are automatized but still receiving intellectual decision support from humans (Gashenko, Khakhonova, Orobinskaya & Zima, 2020, 531-532). Automatization raises competitiveness, reduce the influence of human factor in production and ensure the quality of their products (Popkova et al., 2020, 566). It releases intellectual capital for jobs that require more intuitive and creative touch (Balsmeier & Woerter, 2019, 9).

2.2.4. Optimization

The development of Industry 4.0 is expected to create more value by overall process optimization (Peres et al. 2018, 138). Knowledge creation, automatization and customization all contribute for achieving this optimization. IoT-based network structure and data, that flows in it from various sources are aggregated and processed for the purposes of optimization (Milenkovic, 2020, 4). The process optimization manifests itself as improved efficiency from economic and ecological perspectives and, shorter development and innovation periods (Lasi et al. 2014, 239). Data processing in IoT-based cyber-physical environments provide new knowledge from predictive or current state analytics and, this knowledge with the IoT-system structure may close gaps in control and management activities, improve the relevant key performance indicators and, overall result the increased efficiency in certain activity units or in entire company (Milenkovic, 2020, 13, 18). In ecological perspective, smart environments are visioned to lead to more sustainable solutions. For example, customization can be achieved with intelligent equipment that can decrease water consumption and smart mobility CO2 emissions (Stock et al. 2018, 259). Knowledge creation the intelligent system model enables may translate into strategic preparedness within the people of the organization, which may have optimizing as well. The knowledge gained from integrated and monitored CPS (Lee et al 2015, 20) creates new knowledge and helps gaining better understanding about operation environment as well as intra-organizational processes themselves.

Automation leads to optimization through improved efficiency that is achieved by replacing human labor force with machinery in certain organizational functions and processes. As well, the task re-allocation of social capital followed by automatization has a potential efficiency-improving impact. Balsmeier et al. (2019, 9) state, that the adoption of digital technology has an impact on job descriptions by increasing the demand of high-skilled and decreasing low-skilled work. They, however, also note that although the overall net-effect on employment is positive, the unemployment rate of low-skilled workers may temporarily increase, which makes developing and applying methods for adapting the current labor skill distribution to the digitalization-driven changes as an important investment. In a long run, the investment and the general change in job descriptions may lead to the growth of the efficiency from social perspective as well. Monotonous job tasks have been associated with job satisfaction and health both in physical and mental level (Linton, 2001, 53). Tasks that are challenging enough and require high skills should influence employees by increasing the task interest, elevating the mood and enhancing the performance (Eisenberger, Jones, Stinglhamber, Shanock & Randall, 2005, 770). Fullagar and Kelloway (2009, 609-610) has examined this phenomenon through the concept of flow that describes the optimal state of focus and immersion to the task in hand: tasks that require problems solving skills and allow expressing creativity lead to the experience of flow, which has a reliable and significant relationship to the positive mood and is an important component of psychological well-being. This is consistent with the happy-productive worker thesis, which assumes that the happiness of a worker leads to a better performance and, thus, productivity (Ayala, Ma, Silla, Tordera, Lorente & Yeves, 2017, 1377-1378).

3. MODELING PROFIT ORGANIZATIONS THROUGH SYSTEMS THINKING

Advanced systems skills and systems understanding are defined as two from three types of explicit organizational knowledge (Meso & Smith, 2000, 226). Understanding systemicity is important for interpreting our world as we are pervasively operating with and within complex adaptive systems (Holland, 2006, 1) In the era of Industry 4.0 this importance gets emphasized: as the endeavor is to create IoT-networks by establishing interconnections between different entities, our surroundings are becoming even more systemic. Systems understanding is stated to be a standard requirement for constructing smart environments (Curry & Sheth, 2018, 72). Likewise, as other organizations, for-profits are complex adaptive systems themselves (Kühl, 2003, 5; Holland, 20016, 1). Thus, the consideration of the systemic nature both for-profit organizations themselves and their operational environment was set as a condition when selecting the organizational design approach for the design process for this study. Socio-Technical Systems (STS) design model (Winby & Mohrman, 2018) was selected as it emphasizes the connection of social and technical layers of the organization (Dalpiaz, Giorgini & Mylopoulos, 2013, 1). Likewise, an approach called functional decomposition, that can be utilized for modeling socio-technical systems (Hollnagel, 2012) is presented in this study.

3.1. The importance of understanding systemicity in Industry 4.0

The term cybernetics refers to an idea in which different study fields are fused into a one universal science (Heidegger, 1993, 433-434). Cybernetics was first introduced by Wiener (1948), to refer to the mechanisms with self-regulation capability and the concept forms foundations for such fields of study as AI, neuroscience and reliable communications (Dori & Sillitto, 2017, 209). Industry 4.0's development can be said to be cybernetic. The commonly used dichotomy that separates scientific fields into the ones called ´soft´, ´social´, ´moral´ and ´human´ and the others described ´hard´, ´natural´ and ´exact´ is diminishing in the age of

Industry 4.0. IoT-connectivity aims in comprehensive entity connection and data extraction and, AI-development aims to quantify and mathematically model complex cognitive processes and other psychological phenomena that have been typically perceived abstract and somewhat non-measurable. As an example of the direction Industry 4.0 is heading to, Honkela's project (2017) *Peace Machine* is a concept of a machine that is combining different AI-technologies such as ML, natural language processing, and pattern recognition processing to understand the meaning differences between distinct languages for avoiding linguistic-related misunderstandings and thus, contribute world peace.

Cybernetics has its roots in Bertalanffy's (1945) general systems theory (Dori et al. 2017, 209) and, as Industry 4.0's development can be said to be cybernetic, it can as well be said to lead us towards more systemic world. We already operate as a part or are surrounded by complex adaptive systems, as Holland (2006, 1) points out: understanding how they function is required for embracing the sustainable human growth, predicting changes in global trade, support economic innovativeness, preserving the internet and controlling the internet for threats. Industry 4.0's vision for establishing fully integrated networks that embeds tangible and intangible entities keeps adding more variables to already existing complexity and reducing linearity and separation that is still left. Holland's (2006, 1) points for understanding systems complexity becomes more valid in the era of Industry 4.0 and some of the issues need even more attention like cyber-security, for instance. Curry et al (2018, 72) argues for systems understanding to be a standard requirement for building smart environments, which also indicate the importance of systems thinking in Industry 4.0.

3.2. Organization as a system

Systems thinking is a way for examining and observing things based on systems theory. General principles for system thinking principles embrace the 'big picture' perspective, the balance between long-term and short-term, the recognition of the complexity, dynamicity and interdependency of systems, the consideration both measurable and non-measurable factors and the awareness of being an inseparable part, both an influencer and influenced in the systems (Anderson & Johnson, 1997, 18). An organization is a system in two different scopes: a main system itself and a sub-system within many different scopes of a main system. Understanding the organizations' place in both scales is important to draw a complete picture that considers the influence of both internal and external factors (Anderson et al. 1997, 18-19).

3.2.1. Organization as a main system

Organizations are systems by definition. The use of the word organization is argued to be inflationary in every-day use and its meaning in those contexts often differs from its scientific definition: organization refers to specific form of a social system that can be distinguished from other social systems such as families or nation-states (Kühl, 2003, 5). The definition of social system can be extended to the concept of socio-technical system, that considers the interplay between human, technical and overall organizational layers of the system (Dalpiaz et al., 2013, 1). The consideration of the technical layer is important as digitalization has changed the way organizations operate to a great extent (Winby et al., 2018, 399-400) and Industry 4.0 will assumably push this change forward.

All the general qualities that are defined by Dori et al. (2017, 210) after synthetizing different systems definitions can be identified from an organization, as the following addresses. Organizations are comprised of multiple components and relationships among them. They exhibit unity as well as emergence, which is a characteristic of them they can be identified only as a whole and not any of its separate component. The organization within an organization occurs multi-level. They co-exist with their environment through constant interaction and, as some other systems, have an objective they are expected to reach and for which they are established for.

Organizations are complex adaptive systems. Holland (2006, 1) define complex adaptive systems (CAS) as systems involving large number of interactive and adaptive or learning components called agents. They follow certain function principles: parallel information processing (simultaneous interaction with signal sending and reception), conditional action (an act depends on received signals and may be a signal to another actor), modularity and, adaptive evolutionary long-term change. The complexity of the organizations makes them also intractable systems. Intractable systems are highly heterogenous, are irregular and unstable due to the high change rate and, their descriptions are, on the one hand, elaborate and detailed and, on the other partly unknown (Hollnagel, 2012).

The general importance of systems thinking in the era of Industry 4.0 applies also at the organizational level. Organizations affect our lives to a significant degree but, yet the knowledge about their systemic nature and how their actual mechanisms of function have been primarily gained by incidents and, not taught at as a default even in such fields as sociology, psychology and economics (Kühl, 2013, 5). Incidental knowledge gain is not sufficient. Allen and Starthern (2003, 8) describe complex systems science as 'thermodynamics' for analyzing organizational change: it provides a more scientific approach and a theoretical framework for examining the change of the organization and proving their progress instead of experience-based accumulation of knowledge.

3.2.2. Organization as a sub-system

Systems understanding covers the awareness of the dualistic position of the systems in terms of scope. Internal associations of the system can be examined when they are viewed as main systems, whereas the sub-system scope allows to examine them in relation of their external environment (Anderson et al. 1997, 18-19). As any other system, a profit-organization can take numerous positions as sub-system. The meaningfulness of the scope is dependent of the purpose of the examination. Some exemplary scopes that are meaningful are a for-profit organization as a part of business ecosystem that is defined as a complex and evolving set of firms and individuals interconnected through a global network (Basole, Russell, Huhtamäki, Rubens, Still & Park, 2015, 2), or its coupled data ecosystem.

In Industry 4.0, a for-profit organization will be a part of intelligent ecosystems in different layers, for instance in a scope of a smart city. Kumar (2020, 12-18) introduces the concept of smart city system that has six enabling *'components'*: people, economy, mobility, environment, living and government, all with prefix smart. For-profit organizations fit into two of these categories: people and economy.

Kumar (2020, 18-25) continues, that any city that can reform its existing conditions into a model that follows Industry 4.0’s development can turn into a smart city with many advanced capabilities and value creation opportunities associated to Industry 4.0 and, that the smart city components that driving the transition of these cities are people and economy. From this sub-system perspective, a role of a for-profit organization becomes emphasized as a part that influences to the evolution of the entire smart city system.

Another meaningful sub-system scope of for-profit organizations to examine for this study is them as a relation to their environment, as their existence is rooted to *homo economicus* paradigm. As Cochrane (2019, 13-14) states, our planet is stressed by the non-sustainable presence of humanity and its actions and, this complex and sensitive environment is not saved by just polishing current structures and logistics but new fundamental ways of thinking that change the operation of our mindsets, economics and politics are required. A discipline, that shares the ideas of cybernetics and systems theory have emerged as a response. The Earth System scope Earth System Science (ESS) is a study field that examines the Earth as an integrated system in which natural and artificial elements are both taken into consideration (Simmons et al., 2016, 2041-2042). Pitman (2005, 137) defines ESS as a super-discipline that unifies biophysical and social sciences and views them equally important in order to understand the state and future of Earth. Human contributions and responses is defined as one of the aspects influencing the System Earth (Simmons et al. 2016, 2042).

3.3. Modeling organizations as systems

The study approaches modeling the organization with Socio-Technical System (STS) design perspective. Hollnagel (2012) argues, that modeling intractable systems as organizations are should not be approached with conventional system decomposition methods that are object-based, since they cannot consider the complex dynamics of this type of systems well enough. Thus, modeling organizations is based on mapping their functionality. Profit organizations are very diverse in many of their attributes but, altogether, some underlying general activity can be identified. This general activity is examined in order to facilitate the process of functional decomposition.

3.3.1. Socio-Technical System design approach

This study adopts Socio-Technical System (STS) design approach for the re-design process of a for-profit organization. Socio-Technical Systems are heterogenous, dynamic, unpredictable and difficult-to-control systems, composed from the interplay of technical layer, humans as a social layer and organizational layer (Dalpiaz, Giorgini & Mylopoulos, 2013, 1). The development of STS approach is heavily based on systems theory (Pasmore, 1995, 1-5). The underlying idea behind STS-thinking is that systems design should be a process in where both social and technical factors are considered as influencers of the functionality of the organization (Baxter & Sommerville, 2011, 4). Emery & Trist (1978) present two primary tenets for the socio-technical systems 1. Organization are open systems dependent on affected by the input of environment 2. organizations are more effective, if they are designed the way the interconnectivity of social and technical systems involved is considered.

The emergence of the approach started when a group of therapists, consultants and researchers desired to gain understanding how to utilize better the techniques developed for assisting soldiers damaged by a war (Mumford, 2006, 319). As well, the observations of the better interconnection of social and technological layers brought multi-level benefits by increasing the commitment and motivation of employers, the potential of technology was realized better, the performance of organization increased as well as its adaptation to technological changes are behind the development of STS (Pasmore, Winby, Mohrman & Vanasse, 2019, 68).

Even though many managers understand the importance of socio-technical issues, the usage of STS view and methods has not been widespread (Baxter et al. 2011, 4). The lack of usage is thought to be because it is challenging: examining, modeling and designing complex systems is a complex problem itself (DeRosa, Grisogono, Ryan & Norman, 2008; 1). According to Hollnagel (2012, 13) our mind has a tendency for linear thinking that embraces simplicity and clarity and cause-effect relations. He continues such thinking is an important part for systems design and the roots of linear thinking are reasonable as, in nineteenth century, technological systems were simple and easy-to-understand. Linear thinking is not, however, sufficient: it is necessary to adopt STS-approach for modeling real world socio-technical systems instead of traditional engineering approaches, as they often ignore the social dimension (DeRosa et al. 2008, 1; Wu, Fookes, Pitchforth & Mengersen, 2015, 14-15). The shortcomings of simple linear thinking became widely understood already in 1970's (Hollnagel, 2012, 13). As in general, digitalization has invoked a fundamental change in organizations as well, affecting their societal norms, behaviors and expectations, systems and operation (Winby et al. 2018, 399-400) and in the future it these shortcomings become more and more apparent as the Industry 4.0's development adds complexity in socio-technical systems.

3.3.2. Decomposing the functionality of for-profit organizations

Hollnagel (2012, 6, 44) describes a function as an activity or a set of activities that are needed in order to produce a specific outcome and, consequently, the principle of functional decomposition to understand how a system works. In computer science, decomposition refers to a process in which a complex system or a problem is deconstructed into smaller parts that are easier to examine for understanding, programming, maintaining or designing them (Jiang, Zhu, Li, Zhao, Zhang, Gong & Hong, 2020, 1). As well, the same applies to organization as a system. According to Hollnagel (2012, 4-9) organization should be defined by what does instead of what it is and, as well, due to their intractable nature of socio-technical systems, functional decomposition is a suitable choice to capture, examine and explain the complexity than methods that approach composition through system parts.

There are general patterns behind the diversity of profit-organizations. Profit organizations exist in various forms and, followingly, their specific functionality does too. There are almost indeterminate number of attributes defining them, such as demographic and geographic characteristics making each of them unique. However, their very fundamental structure follows reminiscent patterns. Identifying these underlying general patterns could alleviate the process of functional decomposition.

The very general and core principles of the functions of profit organizations can be derived by examining (macro- and) microeconomic models. The most primary function of the model is derived from a modified *homo economicus* paradigm. The original paradigm contains *homo economicus* agents, model consumers and producers, and assumes these agents to act under full rationality and attempt to maximize profit in terms of personal gain (Hlaváček, Hlaváček, Pelikán, Žák & Havlíček (2013, 14). Some general business models can be used as tools for approaching functional decomposition more practically. Michael E. Porter's (1985) value chain model is an example of such framework. It is generally applicable regardless the diversity that is covered by the term 'profit-organization'. Porter's (1985) model divide the organization functions into primary and support activities.

Homo economicus, however, as such is not the ideal way to approach functional decomposition. As discussed before, it is contradictory with the goals related to sustainable development and new ways to think are needed to achieve fundamental changes. *Homo economicus* influences behind economic change, but over time, it has also become a universal view and a scientific representative of humanity (Ferraro et al. 2013, 127). This view of human being as a purely rational and dispassionate utility maximizer detached from its surroundings is commonly noted to be misleading and partly mis-predictive (Ferraro et al. 2013, 127; Levine, Chan & Satterfield, 2015, 22). Alternative approaches that have emerged to oppose *homo economicus* to challenge as a linear, polarized and misguiding view. They view a human being as a whole by embracing to consider intuition and emotion together with rationality and, bringing the human experience to sustainability by emphasizing creative making instead of producing (Ferraro et al. 2013, 127; Levine, Chan & Satterfield, 2015, 22).

4. MIMICKING NATURAL INTELLIGENCE

The objective of this study is to complement computational AI of intelligent systems of for-profit organizations by extending the mimicry of intelligence to a physical layer of the system. Biomimetic approach was used as a basis of the design process. Imitating biological systems and processes to improve artificial design have long roots in the history of humanity (Vincent, 2009). A study field called biomimetics specifically focuses on systematic imitation process, in where the analogy of biological system is attempted to transfer to artificial design in terms of optimization (Vincent et al. 2006; Cohen & Reich, 2016). Natural information processing systems, such as evolution and human cognition, have the same purpose than information management in any other non-biological context, to function as a sub-system for organizing information concerning the activity of the main system (Sweller & Sweller, 2006, 434, 436).

After the analogy source identification stage of biomimetic design process (see more detailed information on part 6 of this study), the selected biological information processing systems for further examination was human cognition. Mimicking human cognition for problem solving and optimization is not novel per se but, have roots in 1940's (McCulloch & Pitts, 1943; De Jong, 2009). Prudencio and Lurdemir (2015, 1) delineate intelligent computation techniques such as artificial neural networks and machine learning algorithms as a core of intelligent system design. More advanced mimicry of higher cognitive functions is required to produce artificial intelligence systems with the capability to adapt to environmental changes and respond accurately to unexpected situations (Kujala & Saariluoma, 2018, 8). Overall, it has been acknowledged for a long time, that a better understanding of the neural basis of human cognition will have a profound impact to our society through the improvement of practical applications of intelligent machines (Nichlos & Newsome, 1999, 35). As many attempts to develop computational intelligence that has a basis on von Neumann's traditional computer architecture did not result generic intelligent solutions for generic use, the focus of interest turned in imitating biological neural networks to achieve the high-developed cognitive functionality human brain incorporates (Jain & Mao, 1996, 31). Evolutionary Computation (EC), a sub-field of artificial intelligence consists of a set of bio-inspired methods, including artificial neural networks and other intelligent techniques, for problem solving and optimization and, it has been promising in producing successful solutions to many purposes in varying fields and contexts (Eiben & Smith, 2015a**).** EC-techniques are conventionally associated and applied to problem solving tasks on computational level but new insights have emerged to argue for their potential to be applicable to physical level design as well (Eiben, Kernbach & Haasdijk, 2012, 261).

4.1. Biomimetics – inspiration from nature

Humanity being inspired by biology is not a new phenomenon, but mimicking nature has throughout the history influenced our design. beginning from da Vinci's Codex of the Flight of Birds, the original inspiration source of today's aviation technology (Naik & Stone, 2005; Vincent, 2009). It is no wonder nature has provided creativity and innovativeness triggering stimuli for many. Just a quick look into it reveals its ability to create designs close perfect, be the target of the regard the fractals of a romanesco broccoli, the golden ratio in an ammonite shell or the symmetrical hexacons of a beehive. Deeper examination of the nature discloses the same. There are numerous natural mechanisms, processes and structures that have been polished into their current optimal form through evolution over the course of centuries.

Biomimetics is a field of study that examines, imitates and transfers the designs of biological systems to artificial ones in order to optimize them (Vincent et al. 2006; Cohen & Reich, 2016). The field is also known with such names as biomimicry, bio-imitation, bionics or biognosis, as well as "intellectual structure" in Japan and "smart material" in the USA (Hwang et al. 2015). Biomimetics could also be defined as a systematic approach to mimic nature for the purpose of solving problems related to artificial design. Numerous cases of similar modeling and application of natural analogies can be found without a structured and methodical biomimetic process of study as their basis. Examples from such projects are Gottfried Semper's architecture that was influenced by the work of naturalist George Cuvier and Velcro invented by George de Mestrals after his cockle burrs examination (Marshall & Lozeva, 2009) Cohen et al (2016) distinguish the less systematic approach as bioinspiration or bio-inspired design (BID).

This optimization process of evolution is existent in every biological system, regardless of its scale. As the study of biology itself, biomimetics can be roughly divided into macro-, micro- and nano scale. The mimicry process can be targeted to a complete ecosystem or, a more limited and detailed part within it, such as a behavioral process like self-organization or a material structure of a single organism (Naik & Stone, 2005; Zari, 2007).

4.1.1. Why biomimetics?

Biomimetics is based on analogical reasoning. The key idea behind analogical reasoning is to transfer an attribute from one context called source into another called target (Gentner, 1983) Selective aspect combination between different sources of domains to create totally new useful analogies is perceived as a fundamental mechanism of creativity (Levine, Chan & Satterfield, 2015). Cohen et al. (2016, 20) describe biomimetics to be, by definition, analogical transfer of design knowledge from the source, that is a biological system, to the target, that is an artificial design. Nature has developed design solutions to many ‘problems’ that are similar with the ones humans face (Fisch, 2017, 797). As this analogical similarity between natural and artificial problems has been noticed, it has resulted to many successful biomimetic applications. Structural design application examples can be found from architecture and materials technique: fluid-drag reduction swimsuits took inspiration from shark skin (Hwang, Jeong, Min Park, Hong Lee, Wook Hong & Choi, 2015), the shape of Japanese bullet train design was optimized by mimicking kingfisher beak (Cohen et al. 2016), wind turbines imitate humpback whales (Fish, Weber, Murray & Howle, 2011) and stable building structures were copied from the backbone of turban shells (Hwang et al. 2015). Besides physical biological structures, in other cases the inspiration source has been a mechanism, or a process found from nature. Examples for this type of imitation include biomimetic robotics (Shahinpoor, 2003; Jiang et al. 2014) and computational algorithms that are based on some biological mechanism such as swarm intelligence (Abraham, Guo & Liu, 2006; Garnier, Gautrais & Theraulaz, 2007) or evolution itself (Whitley, 1993; Bäck, Hammel & Schwefel, 1997).

Nature has a simple, yet extraordinary mechanism for self-organization, namely evolution. Fogel (2000, 26) describes evolution as a fundamental biological force that has no intrinsic purpose but originates from physical laws and, that interlinks every organism together through the iterative process of variation and selection Natural harmony, that manifests itself as a synchronized co-existence of organisms and self-adaptability whenever the harmony is disturbed, is a result of evolutionary processes that are present in these organisms. Their processes, structures and mechanisms have gone through evolutionary iterations, that have preserved worthwhile and eliminated redundant functionality. The fundamental premise behind biomimetics lies herein: through evolution, natural systems have been refined into the state of optimum, to achieve the maximum performance with minimal amount of resources (Bhushan, 2009; Fisch, 2017, 797).

The core evolutionary mechanism strives for ‘the survival of the fittest’ in an environment with the competition for limited resources (Eiben et al. 2015b, 25). In other words, the mutation-selection iteration of evolution aspires to mold the organism to be optimally compatible with its surroundings. Such continuous process of adaptation produces mechanisms, processes and physical structures that are effective in their operation environment. Effectiveness improvement examples for biomimetic design are reduced costs due to extended life cycle (Antony, Grießhammer, Speck & Speck, 2016, 2100) and timely more accurate processes (Wu, Jiang, Li, Zhou, Zhang, Zhi & Gao, 2020, 10-11).

The effectiveness of biological structures, the analogical resemblance between artificial problems and natural ones the biological structures have evolved to provide a solution, as well as the successful bio-inspired applications thorough human history indicate that biomimetics could be a promising study field for design, problem-solving and optimization. There is, however, development points in the field itself. Biomimetics is said to be ethically distinct, yet it currently still driven by the ideas of capitalism and lacks critical reflection of its methodologies, which both seem to result from mindsets still influenced by *homo economicus* paradigm (Fisch, 2017, 804),.

4.2. The mimicry of human cognition

During the biomimetic design process of this study, potential analogical similarity between human cognition and artificial information processing in Industry 4.0 was recognized (see chapter 5.3.2.). After identifying the potential analogy source, the following step was the familiarization of its mechanisms for the abstraction into principles that can be further transferred into a technical solution. The familiarization with the related literature revealed the long roots of former imitation study of human cognition.

How human brain works has been an interest of study for more than a century and, especially, during the past two decades the interest has growing rapidly by around 50 000 neuroscientists giving their contributions (Sterling & Laughlin, 2015, XIV). The study field of Artificial Neural Networks (ANN) that is based on connectionist approach of human cognition (Medler, 1998, 21) and that specifically focuses on the imitation of the neural activity of human brain is associated in the literature to origin from McCulloch and Pitts' (1943) work. Albeit the terms biomimetics and ANN do not commonly co-exist in the literature, the study of ANN clearly follows similar process than systematic biomimetic design: the abstraction of the mechanisms of human brain and transferring the mechanisms into a practical solution for optimization or solving a problem.

4.2.1. Artificial Neural Networks (ANN)

The study of Artificial Neural Networks (ANNs) focuses on the modeling and simulation of human brain and how it processes information. The origins of the concept is associated to McCulloch and Pitts' (1943) work in which they presented a mathematic and logic -based models of neural activity. Over the course of time, the development of the study of ANN's has gone through four stages (Zhang, 2010, 3-5). ANN's are nonlinear information processing system that is composed of numerous processing units and characterized as self-adaptive, self-organizing (Ding, Li, Su, Yu & Jin, 2013).

The study of ANN's is influenced by the connectionist models of human brain and cognition (Medler, 1998, 21). Traditional approaches for human cognition are based

Newell and Simon's (1976) physical symbol hypothesis that views cognitive architecture as patterns of information represented as manipulatable symbols (Medler, 1998, 20). Traditional approaches are more sequential of their nature and include the most generally accepted 'stage theory' developed by Atkinson & Shriffin, (1968) and Craik and Lockhart's (1972) 'levels-of-processing' model (Huitt, 2003). Connectionist approach (Rumelhart & McClelland, 1986) differ from these models and emerged to challenge them by viewing the cognitive architecture as a vast network of interconnected units (Fodor & Pylyshyn, 1988) and, assuming that information is transformed by parallel processing of sub-symbols based on statistical properties instead of logical rules (Medler, 1998).

The motivation behind ANN research and development is that evolution has polished several desirable attributes for human brain that cannot be found in traditional von Neumann computer architectures, such as parallelism, distributed computation and representation, adaptability, ability to learn and generalize, low rate of consumed energy, contextual information processing and high fault tolerance (Jain & Mao, 1996, 31). Even seemingly simple decisions such as choosing an apple for consumption are, in fact, based on a fairly complex cognitive process, as Nichlos et al. (1999, 35) explain. They describe the process to begin from the scene construction by filtering irrelevant information, evaluating the information through perceptual and affective interpretation, deploying spatial attention, discriminating sensory stimuli and, combining immediate sensory information with previously learnt information. After the scene has been constructed, the appropriate behavioral response is planned and executed (Nichols et al. 1999, 35). In cognitive science, connectionism aims to explain this higher level brain functions such as attention and reasoning (Medler, 1998, 20).

The basis of the connectionist model of human cognition and, followingly, the study of ANN is consistent with brain research (Huitt, 2003). The basic neurobiological structure of human brain consists the body of neuron cell called soma (consists of nucleus and cytoplast) dendrite (thousands in a single neuron, receives signals from the other neurons, neurite (sends signals to other neurons, may have several branches connected to other neurons) and synapse that connects two neurons to each other (Zhang, 2010, 5). Medler (1998, 22) lists six basic functional properties for neurons that are:

1. Input: signal reception from the other neurons and from the environment
2. Integration: input manipulation and integration
3. Conduction: conduction of the integrated information
4. Output: information transmission to other neurons or cells
5. Computation: information mapping one type to another
6. Representation: subserving the formation of internal representations

Following the connectionist parallel-distributed processing models (Rumelhart, Hinton & McClelland, 1986; Bechtel et al, 1991) and neurobiology (Huitt, 2003) ANN's are processors that are massively parallel distributed and, that are built from processing units representing neurons with the capability to learn and store experimental knowledge for the use (Floreano, Dürr & Mattiussi, 2008, 47; Kalu & Madueme, 2018, 1469). The research has resulted various ANN models (Chung, Yang, Lee, Lee & Moon, 2017, 81). However, a typical ANN model consists of three layers: input, hidden layer and output layer (Kalu et al., 2018, 1469). The sophistication level of ANNs varies from simple neuron models of a weighted sum of income signals that is transformed by a static transfer function to ones with discrete- and continuous-time dynamics (Floreano et al. 2008, 47).

ANN-based models are suitable for generic-use and can deal with large-scale complex problems as they do not require any detailed information of the system or specific analytical equations (Hsu & Chen, 2003; Mohanraj et al., 2015, 150). They have been useful in various contexts for many purposes such as simulation, modeling and estimation in thermal analysis (Mohanraj, Jayaraj & Muraleedharan, 2015, 167), fault classification and detection for power system location (Kalu et al. 2018, 1467, 1479) and, forecasting and construction planning (Hsu & Chen, 2003, 1941, 1947-1948) and prediction for energy efficiency (Shahid, Rappon & Berta, 2019, 1).

5. METHODOLOGY

The approach of this study is a design research, in which scientific knowledge is combined with the design process. Biomimetic design process stages formed a basis for the design, as it provided a suitable approach by sharing similarities with the mimicry process behind computational AI applications that imitate human cognition. In recent years, the field of biomimetics has gone towards more systematic direction through the development of tools, methods and the overall design process. Cohen and Reich's (2016) *Biomimetic Design Method for Innovation and Sustainability* provided a comprehensive and detailed overview of biomimetic study and its methodology. In addition, the work suggested a general process framework for biomimetic design, which was adaptively applied to this study.

Literature related to organizational design was examined to address the conditions needed to take into consideration with the design target of this study, which was a single for-profit organization. Organizations are complex adaptive systems and complex systems science is stated to provide a scientific approach for their examination instead of incidental knowledge gain (Allen et al., 2003, 8). Overall, systems understanding is becoming important for interpreting the world that is emerging into more systemic form due to the current integrative development. Socio-Technical Systems (STS) design approach and classical STS design process introduced by Winby et al. (2018, 403) was adapted as a complementary approach to biomimetic design to consider the design target of the study.

The design process framework was constructed by embedding elements from Cohen et al.'s (2016, 21-25) general biomimetic framework and from Winby et al.'s (2018, 403) STS design model. The design process of this study is divided into four general stages: the formulation of the problem statement, the abstraction of the solution, the concretion of the solution and the evaluation of the solution. Each stage includes a set of activities that are described in the next sub-chapter. Chapters from. will describe the actual design process of this study.

5.1. Scientific design

This study is a design research. The basis of the design research is in scientific design that fuses the elements of a research and a design process by building onto scientific knowledge using both intuitive and non-intuitive methods (Cross, 1993, 19). Design sciences, such as the study of AI, aim to examine the behavior of designed artifacts under different conditions (Collins et al., 2004, 17). Barab & Squire (2004, 3) Design research aims to gain understanding of the complexity of real-world practice (Barab & Squire, 2004, 3). The ‘design methods movement’ emerged after it was noted that certain design in such fields as architectural, engineering, material and behavioral sciences have scientific foundations and, that intuitive design methods are not sufficient for modern complex industrial design (Cross,1993, 19).

The relationship between the science and design can be described as making science visible by applying scientific knowledge into practice through design (Willem 1990, 43-47; Cross, 1993, 20). According to Edelson (2002, 8), design research is about filling the gaps to complete the theory behind the design, which is required in order to meet the practical demands of design. Another benefit of design research Edelson (2002, 8) brings up is, that the design process exposes inconsistencies naturally more effectively than analytical processes do because of the conflicting guidance of the theory. The focus in design research may about forming a new theory that give characteristics for the design for its practical application (Barab et al., 2004, 3).

The selected research approach meets some specific needs of the objective of the study that was to attempt to complement computational AI of intelligent systems of for-profit organizations by extending the mimicry of intelligence to a physical layer of the system. Research design approach has emerged from the recognition of the insufficiency of intuitive design methods for the complexity of industrial design in the modern era. Complexity has grown due to digitalization and keeps going as the Industry 4.0’s development goes forward. Likewise, the development of Industry 4.0 involves all of those sciences, that have strong scientific foundations used as examples by Cross (1993, 19), that benefit from a design process with a scientific touch: architectural, engineering, material and behavioral. Altogether, using design research approach in this study helps with reflecting the theory of Industry 4.0 with the practice, which was stated as an important gap to close with big data (Ekbia et al. 2015).

5.2. Socio-Technical System design with biomimetic approach

The design framework of this study has a basis in biomimetic design. Biomimetic design process, defined by Cohen et al. (2016, 21-25) includes five stages: problem definition, analogy source identification, solution abstraction, solution transfer and lastly, evaluation and iteration. These design process stages, and their descriptions are shown in figure 2.

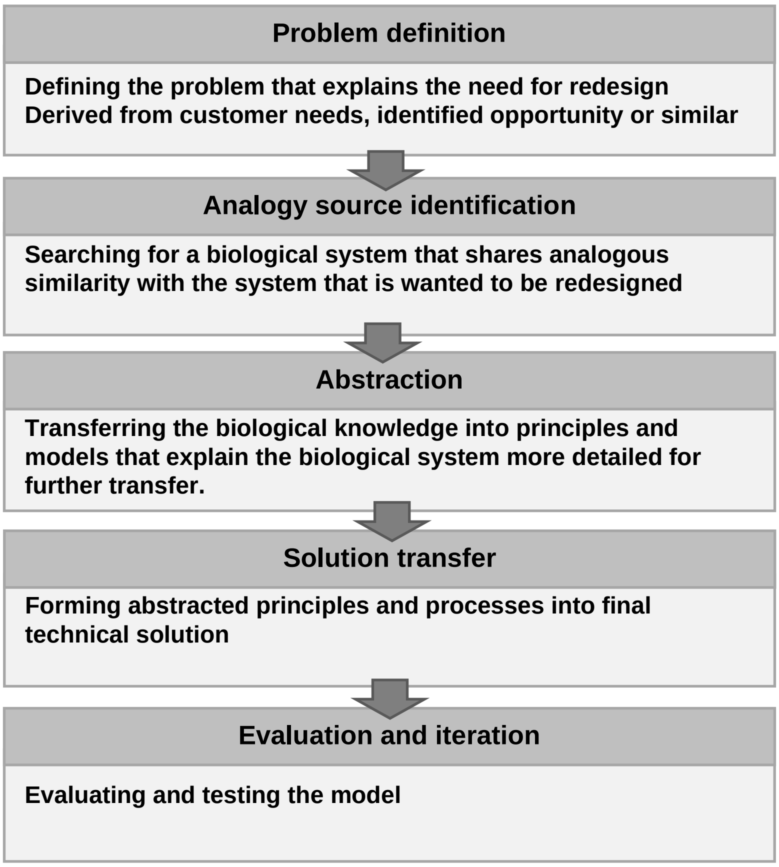

Figure 2: Biomimetic design process stages (Cohen et al. 2016, 21-25)

It was as well examined, what needs to be taken into consideration with the design of the selected design target of the study, that is, a for-profit organization. Systems thinking has an importance in understanding the activity of complex adaptive systems, which organizations are themselves as main-systems and a part of as sub-systems (Kühl, 2003, 5; Holland, 2006, 1). Along with the development of Industry 4.0 the world is becoming more systemic and complex. As well, understanding systemicity is named as a standard requirement for designing smart environments (Curry et al., 2018, 72). Thus, the approach selected for the study was Socio-Technical Systems design, which considers the intertwine of social and technical layers of the organization and is influenced by systems theory (Dalpiaz, Giorgini & Mylopoulos, 2013, 1; Pasmore, 1995, 1-5). The STS-framework (Winby et al. 2018, 403) adopted for the study is presented in figure 3.

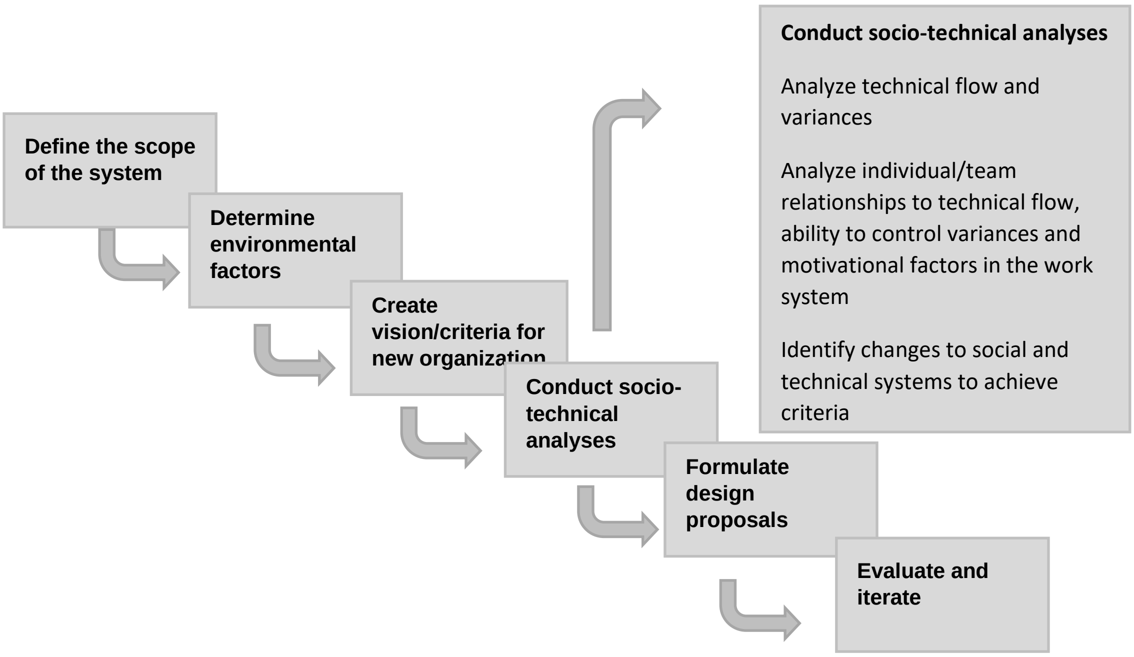

Figure 3: Simplified socio-technical systems (STS) design process (after; Winby et al 2018, 403)

Figure 4 shows the design framework for this study. The framework was constructed by adapting and merging the elements from Cohen et al.'s (2016, 21-25) biomimetic design stages and Winby et al.'s (2018) STS design model. The design process consists of four general stages: forming the problem statement, abstracting the solution, concretizing the solution and evaluating the solution.

The problem statement stage merges the four first steps from the STS-model (after Winby et al. 2018, 403, see figure 3) together. The problem statement will be formed based on systems scope definition, environmental demands and socio-technical analyses. After these are defined, the problem statement is derived from this system-environment analysis, which also sets criteria for the new design.

After defining the problem follows the solution abstraction stage. Based on the system-environment analysis and the problem statement, the criteria for new design is defined. The stage also covers the conduction of socio-technical analyses, as described in the STS design process (see figure 3). The following step is to identify the biological analogy source for mimicry. Once the potential analogy source has been identified, it will be abstracted into principles for further transfer.

The third stage of the design process is to concretize the solution. This stage includes transferring the principles, mechanisms and processes of the mimicked biological system into a technical solution (Cohen et al., 2016). Final stage is the evaluation of the solution.

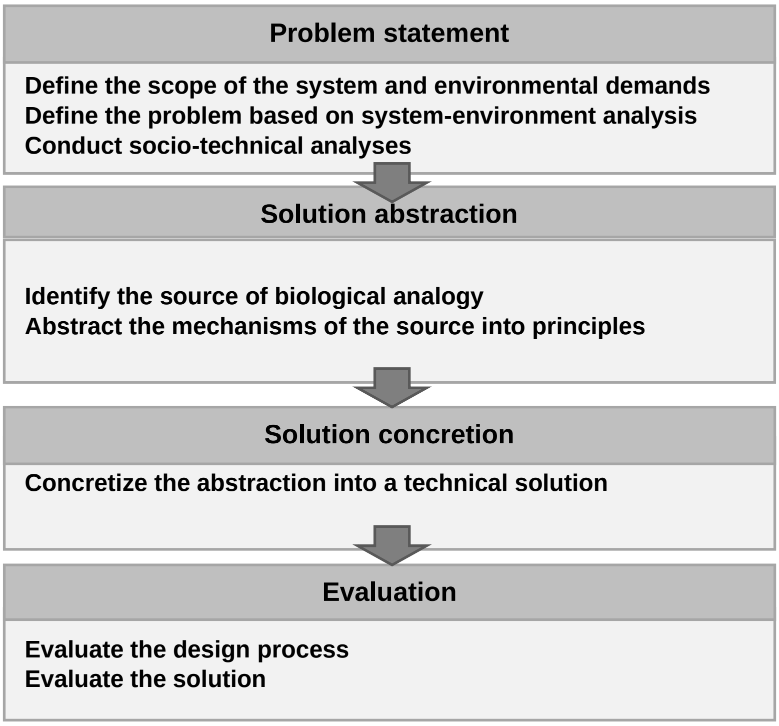

Figure 4: Biomimetic process for socio-technical systems (adapted from Cohen et al. 2016, 21-25; Winby et al. 2018, 403)

6. RESULTS

This part of the study describes the design process of this study step-by-step. The design process of the study (see figure 5) included four general stages: problem statement, solution abstraction, solution concretion and evaluation. Each stage covered a set of activities, both from biomimetic and socio-technical system design processes. Each following sub-section of this part of the study describes the general stage and design activities included to the stage in question.

6.1. Problem statement

The design process began from the problem statement. Well-defined problem is a crucial part of any design process but, in biomimetic approach its emphasis may be even greater as the problem statement impacts on how well the biological mimicry source can be bridged to the application domain (Cohen et al., 2016, 21). Defining the system scope and determining environmental demands are presented as first two stages of classical STS design process by Winby et al. (2018, 403). These activities were considered for the problem statement formation of this study.

6.1.1. System redesign for profit organizations

The objective of this study was to attempt to complement computational AI of intelligent systems of for-profit organizations by extending the mimicry of intelligence to a physical layer of the system. The problem statement step began from the definition of the system scope of the design target. The selected scope for the design was a single for profit-organization. The design target was defined very general on purpose, as it was wished to design a solution that has a generic applicability. Regardless of the variety in which for-profit organizations exist, it is possible to generalize their operation with the methods like functional decomposition (Hollnagel, 2012) and general business frameworks such as Porter’s (1985) value chain models.

6.1.2. Environmental demands

Environmental demands are derived from the development of Industry 4.0 and sustainability questions concerning the for-profit organizational operation. Likely, there are other environmental demands such as regional regulations and policies that could set condition for the design. As an example, The General Data Protection Regulation (GDPR) of European Union directs the collection of personal data of the citizens of EU (Regulation (EU) 2016/679). Such factors were, however, excluded from this study to design a generic applicable solution.

The development of Industry 4.0 can be generalized as the design of intelligent systems. Intelligence-enabling technologies and concepts were examined in the part 2 of this study and three intelligence attributes were identified: IoT-connections, big data and AI-applications. The development is centered around these attributes and they set adaptation pressures for for-profit organizations. Positioning in a competitive market environment is a key success factor for the for-profit organizations which requires quick reactivity to environmental changes in order to survive the competition (Kotler et al., 2010, 12, 44). In Industry 4.0, efficient big data management is, for example, considered as key competitive advantage (Cavallinas et al. 2016).

Sustainability perspective sets environmental demands as well. The logic behind the homo economicus paradigm assumes that humans as rational beings preferably choose strategies that maximizes their very personal gain, which is believed to be a significant reason for the unsustainable state of the planet and damages it has caused to our environment (Ferraro & Reid, 2013, 127). For-profit organizations' existence is rooted to the homo economicus paradigm (Hlaváček et al., 2013, 14), which makes their existence contradictory with sustainability development goals. The current state of our environment is alarming, and it is argued that fundamental changes are needed to reverse the situation (Cochrane, 2019, 13-14). Industry 4.0's vision is believed to promote sustainable growth (Jagadish et al. 2014). Consequently, adapting the changes of Industry 4.0 is not only important for the survival for of the for-profit organization itself but, as well the environment.

6.1.3. Socio-technical analyses

Winby et al.’s (2018, 403) model include a step for conducting socio-technical analyses, which include the analysis of technical flow and variances, the social relationships to technical flow, their ability and motivational factors to control variances and identifying changes to social and technical systems to achieve criteria.

Technical flow and variances are centered to big data’s incompatibility problems with traditional data management tools, as well as the placement of IoT-connections. Big data incorporates information that could be turned into new insightful knowledge concerning the organization’s processes, environmental factors and their mutual relationship. Getting access to this knowledge is also motivational factor for the people within for-profit organization for the re-design system. Accessing to the knowledge could improve the strategic competencies of and organization in social level, as well as, giving insights from the environmental relationships to cultivate sustainability. Changes needed: Industry 4.0’s development points: IoT-connectivity, seamless big data exploitation and AI-application placement. However, changes are needed as well in mindsets of people. The need for fundamental change is identified to the change of *homo economicus* paradigm and replace it with alternative approaches.

6.1.4. The need for more intelligence to create more value

Intelligence seems to be a desired quality and key component in Industry 4.0, and it is assumed to manifests itself in such ways than predictability, environmental reactivity and complex problem solving that could solute many problems. The concept of AI, however, seems to be centered around computation, although desired intelligence is more comprehensive.. For achieving more comprehensive intelligence, this study attempts to extent the concept of AI beyond computation to consider big data and IoT-integration as well. The goal is to design a cyber-physical system, in where the intelligence is present both in digital and physical layers. The extension is approached with similar path the computational AI follows. As it mimics cognitive functions, biomimetics design process is used.

6.2. Solution abstraction

The stage of solution abstraction merges together the analogy source identification and abstracting its mechanisms into principles. Together with the following stage, this is a part of the solution formation in STS-design process.

6.2.1. Biomimetic analogy source identification: human nervous system

After the problem definition stage, the following step in Cohen's et al. (2016) biomimetic design process is to identify the analogy source, which means to find a biological system that denotes analogous similarity with the target system. Cohen et al. (2016) state a requirement for using searching algorithms and techniques for information retrieval from databases in this stage. Chiu and Shu (2007) have an alternative method is based on natural language processing and the aim is to identify lexical paths between words that describe functionality. The goal is to identify the path between the one word that is related to the problematic activity of the artificial system under optimization and, the other word that covers similar functionality but has a biological connotation and may, thus, reveal a potential biological system with an analogous match. The word with biological connotation becomes a keyword for searching the biological systems.

In this study, the identification process was performed with keyword searches based on the method that adapted ideas from Chiu et al.'s (2007) natural language processing approach. Searches were performed by using LUT Primo (a search engine of Lappeenranta University of Technology) and Google Scholar search engines for scholarly literature. The keyword used were formed as follows:

1. A problematic attribute of the design target, that needed to be solved was selected: *data management*
2. The lexical path between the activity *data management* and context-free general terminology that covers the activity *data management* was identified: *information processing*

3. The prefix ‘natural’ or ‘biological’ was added to target the search for information processing systems found from nature: *natural information processing*, *biological information processing*

The search performed with the keywords *natural information processing* resulted an article ‘*Natural information processing systems’* by Sweller et al. (2006), that introduces the principles of human cognition and evolution. The process of analogical reasoning that is behind biomimetics, lead to the identification of analogous similarity with data management and information processing based on human cognition was considered, leading to the following observation:

Analogously, a human brain is like a well-performing big data processor with its highly developed cognitive functions. It continuously receives massive amounts of multi-structural information through the senses. It is capable of filter, combine and interpret this information and, make decisions and perform actions based on it. Human cognition has an ability to process the information it continuously receives without specific information acquire initiations and, as well it is able to search for perform searches for specific information.

This observation revealed analogical similarity between the target and the source. Human cognition incorporates many characteristics that are desired for to create more value with managing big data: the ability to effectively and meaningfully acquire, curate and exploit voluminous, multi-structural information. Thus, human cognition was selected for more detailed examination as a potential biological analogy source in biomimetic design process. As current AI-applications mimic the cognitive processes and, the focus of the re-design process was to expand the intelligence to the physical layer of CPS, the attention from cognition itself was shifted to its physical structure: human brain.

The basic concepts of human cognition were familiarized with the literature from various biological and psychological fields, including neurosciences, anatomy, biomedicine and cognitive sciences. Another remarkably important field the information was gathered from was computational sciences, specifically the study of Artificial Neural Networks. The study covers decades long research of neural networks that shares similarities with biomimetic design process. Getting acquainted with the mechanisms of human brain and overall human neural network revealed that, comprehensively, the architecture of human nervous system might provide structures and mechanisms for adding intelligence to the other attributes. The central concept is the process of homeodynamic regulation for the maintenance of internal stability, in which the human nervous system plays a central role. The following sub-chapter 6.2.3. explains the homeodynamic regulation and its elements more detailed.

6.2.2. The role of human nervous system in the regulation of internal stability

Key mechanisms, processes and structures of the selected biological system were examined and abstracted into principles to explain its functioning and analogical fit with the target system (Cohen et al. 2016, 23-24). The selected analogy source of this study, that is, human nervous system has an integrative role in maintaining internal stability in human body (Jänig, 2006, 1-2). The abstraction process was approached with the examination of the concepts that describe the internal stability of human body: *internal milieu*, *homeostasis* and *allostasis* (Schulkin, 2004, 2; Davies, 2016, 2; Marshall, Gallacher, Jolly & Rinomhota, 2017, 25). Derived from these concepts, *homeodynamic regulation* refers to the stability maintenance process itself. Homeodynamic regulation requires basic elements: *receptors*, *effectors*, *control center* and a *communication channel*. These are the key concepts of the selected system and, in the following, they will be explained more in-depth as a part of the abstraction process.

Homeostasis and ***allostasis*** are concepts that are related to the internal stability of human body. Homeostasis, that origins from the term internal milieu, is widely accepted and used term in biological and physiological sciences for referring to the relatively stable internal state of living organisms, that is maintained despite of occurring internal and external disruptions (Schulkin, 2004, 2; Davies, 2016, 2). In recent years, however, the concept of ‘stasis’ and its validity and sufficiency to describe the capability of maintaining the parameter stability in organisms that change over time have been increasingly questioned (Marshall, Gallacher, Jolly & Rinomhota, 2017, 25), resulting the emergence of alternative or extensive concepts such as homeodynamics and allostasis. Whereas homeostasis traditionally describes the short-term physiological adaptation of organisms, allostasis emerged to distinguish to describe the stability that is maintained despite of long-term adaptive evolutionary change (Schulkin, 2004, 3). An alternation for homeostasis is the concept of homeodynamics that considers allostatic process as well (Marshall et al. 2017, 6).

Homeodynamic regulation refers to the process of the maintenance of internal stability (Marshall et al. 2017, 9-10), The basic homeodynamic system involves certain components: receptors that cover sensory functionality for monitor the environment for changing stimuli, a control center that receives information from receptors about the changes, effectors the information about the stimulus analyzed in the control center is forwarded for producing an effect to counter the disruptive stimulus and, a channel that enables the communication between the receptors, effectors and the control center (Jänig, 2006, 1; Marshall et al. 2017, 9-10). The effect acted by the effector to diminish the impact of stimulus is called negative feedback (Marshall et al. 2017, 100). Figure 7 illustrates how the process of homeodynamic regulation proceeds.

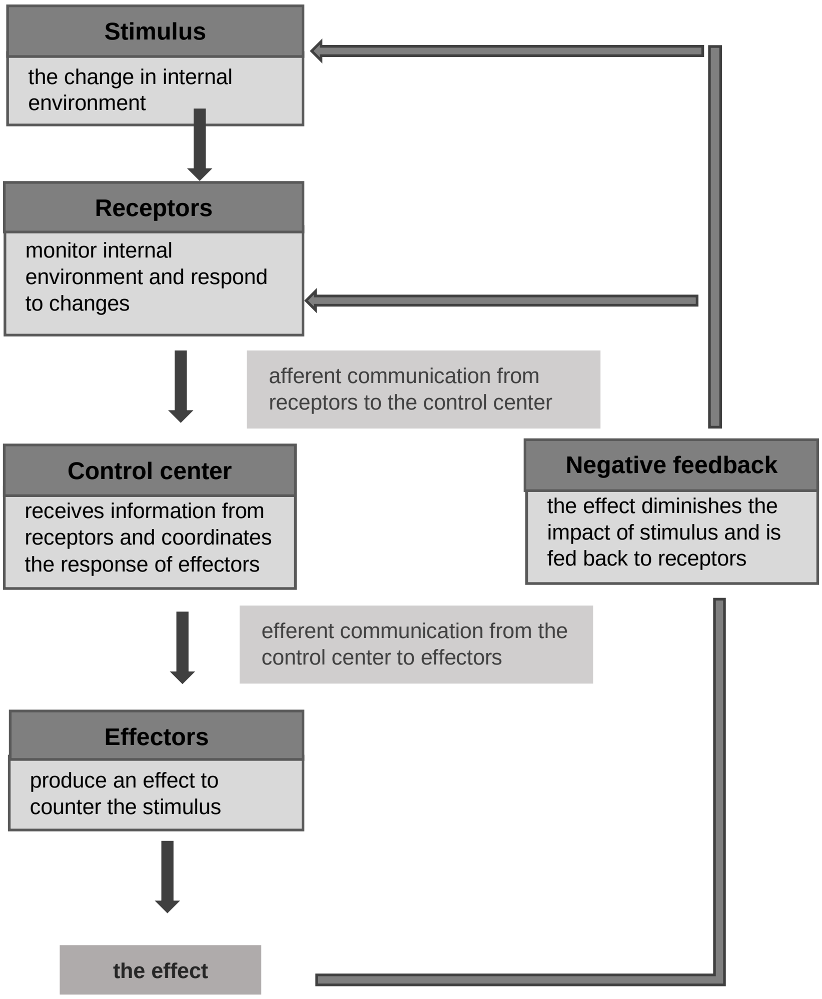

Figure 5: General homeodynamic process for maintaining internal stability of human body (after Marshall et al. 2017, 10)

Receptors are an element of homeodynamic regulation that monitor the environment for internal and external stimuli (Marshall et al. 2017, 9-10). Monitoring is enabled with the sensory functionality they cover. The development of highly refined sensory systems, that also include sensory organs that enable such senses as hearing and vision, is relative late occurred evolutionary adaptation of vertebrates for the need to draw discriminations between different stimuli (Moller, 2003, 3).

Effectors that consist of organs, muscles and glands in a human body, are responsible for producing corrective actions against the disrupting stimuli (Marshall et al. 2017, 9-10, 101). The effect is based on the analysis conducted in a control center from the information received from receptors. The produced effect's is called negative feedback, as it diminishes the impact of stimuli. (Marshall et al. 2017).

A control center is required element for homeodynamic process for information coordination and analysis between the receptors and effectors. The core task of the brain is the regulation of internal stability by tuning the internal parameters to improve overall stability and economy (Sterling et al. 2015, XVII, 44-45) The functions that are contributing the maintenance of internal stability of human body are under a control of brain (Jänig, 2006, 1-2). The monitored information by receptors is sent for the analysis to the brain, which, based on the analysis, exerts a command to effectors for the production of a timely and a sufficient effect to counter the stimulus (Marshall et al. 2017). The information flow between the receptors, the control center and the effectors enables human body to adjust its performance to various internal and external demands (Jänig, 2006, 1-2).

Autonomic nervous system and endocrine system are the main communication systems for information flow to facilitate the internal stability in human body (Marshall et al. 2017, 10). As all living organisms, humans are in a constant interaction with their environment by receiving continuously signals from the environment via sensory system and respond to these signals with theirsomatomotor system (Jänig, 2006, 1). The information flows through these systems as afferent and efferent communication (Jänig, 2006; Marshall et al, 2017) Through the autonomic nervous system and endocrine system, the receptors send afferent signals about the monitored stimulus towards the brain about which exerts an efferent signal to the effector for the effect production of an effect as a countermove for stimulus (Jänig, 2006, 1-2).

Table 1 summarizes the concepts of a biological system that were abstracted in this study. It presents each abstracted concept and their principles of function.

Table 1: Summarization of the abstracted concepts

Abstracted concepts	Function principles
Homeostasis	The state of internal stability in short-term
Allostasis	The state of internal stability in long-term
Homeodynamic regulation	The process for maintaining internal stability both in a long run and short run
Receptors	Monitor internal environment, respond to changes
Control center	Receives information from receptors (afferent signals), analyzes information, sends commands (efferent signals) for effectors
Effectors	Produce an effect to counter stimulus
Autonomic nervous system	Communication channel for signaling, integrative element for maintaining homeostasis

6.3. Solution concretion

6.3.1. Mimicking the structure of homeodynamic regulation system

Helmold (2019, 161) describes the study of Artificial Intelligence as one, that examines intelligent agents, devices that can analyze their environments and act based on their analysis to maximize the change to achieve their goals. Added intelligence for the profit organization is expected to achieve through system re-design, that is guided by the idea of homeodynamic regulation. In biological sciences the concepts of homeostasis and allostasis refer to the relatively stable state that is maintained despite of internal and external disruptive changes both short-term and in a long run (Jänig, 2006, 1). Homeodynamic regulation is a process that maintains the stable internal state. Enabling homeodynamic regulative process requires the following components: effectors, receptors, a control center and a communication system. Some of these components have counterparts that share the analogical similarity with the development of Industry 4.0. The system re-design suggestion with details is presented in the following sub-chapters will exploit the components of homeostatic regulation as a framework. It addresses the placement of Industry 4.0's central technology concepts, as well as, offer additions for achieving added intelligence through a complete regulative system model for profit organizations for the maintenance of their internal stability.

6.3.2. A function model of the physical layer of CPS

Conceptually, an information system is viewed as an equivalent for the cyber layer of a CPS in this study. The design begins from constructing a model of the physical layer of the system. It is an essential part of the design as the physical layer model is what the information system architecture will be based on. It facilitates the placement of the components for the architecture re-design. This study suggests constructing a physical layer model that is based on functionality. Functionality instead of objectivity describes better the complexity of intractable systems such as socio-technical systems (Hollnagel, 2012) like profit-organizations are. As well, functionality is general and thus, the method is applicable regardless of the the specific characteristics of the profit-organizations, as they greatly vary by many attributes. General business models such as Porter’s (1985) value chain model can be used with help to chart define the functions for the profit-organization. Function is an activity or set of activities (Hollnagel, 2012). Figure 6 shows a simple exemplary map of functions of physical layer.

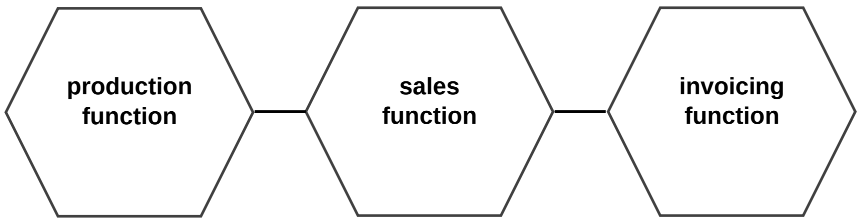

Figure 6: Exemplary model of function-based physical layer analysis

6.3.3. Digital shadows for physical layer functions

After mapping the physical layer functionality, the following step is to establish their digital representation. Stock et al. (2018, 256) described the process of transferring real production processes to the virtual world as the application of digital shadow (figure 7). Analogously, in comparison with human body, digital shadows are the basis for organs, function performers, as in physical layer functions. Svenaeus (2010, 179, 195) has examined organs from phenomenological perspective through Heidegger's ideas and, emphasizes their place as a part and a belonging of a totality and, functional nature of them: *'Organs make us able or, or not able, to do things, but they do not act themselves, they perform functions.'* Data that already exists about the physical functions within a profit-organization is utilized to form the digital shadow.

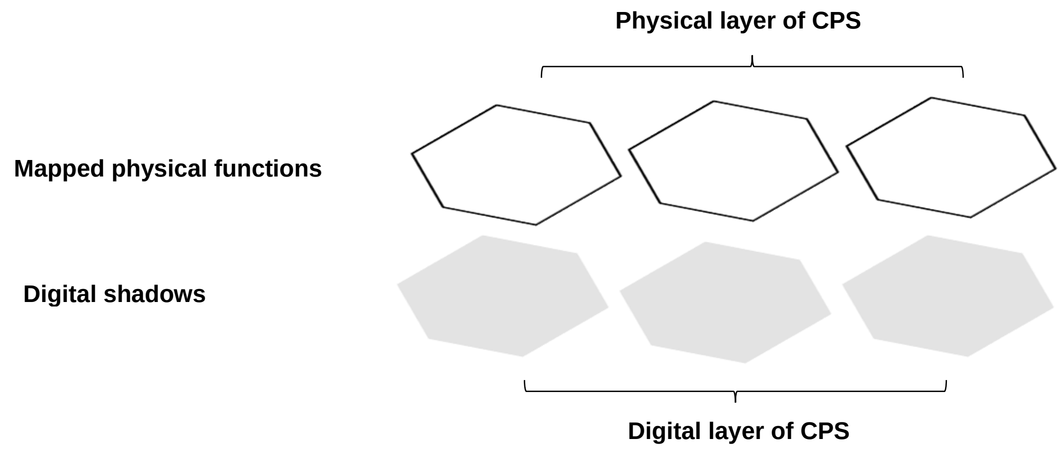

Figure 7: Digital shadows for physical layer functions

6.3.4. Receptors for the completion of digital twins

From technological perspective, a complete digital representation of the physical layer function is conceptualized as Digital Twin (Stock et al. 2018, 256; Peres et al. 2018, 139; Kaur et al., 2019, 5). The architecture model suggests that each physical function should have a complete Digital Twin in cyber level of CPS for maintaining internal stability. The completeness of digital twins is achieved with receptor placement. Receptors are an enabling part for the process for maintaining internal stability: they monitor internal conditions and respond to changes (Marshall et al. 2017,). The architecture suggests including a sensory system for receptor activity.

First part of the sensory system is a sensor that are placed on physical level functions. The sensors collect data from physical layer and with their adequate placement to the physical functions, digital shadows can be turned into complete digital twins.

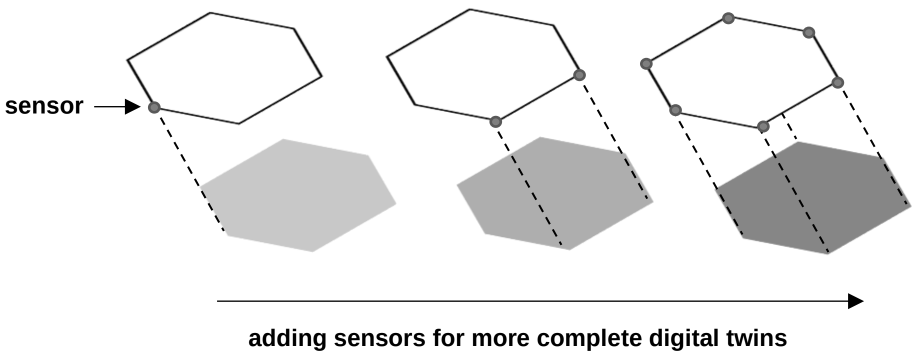

Figure 8: The placement of sensors for the completion of digital twins

Figure 8 illustrates the model with completed sensors activity. Placing sensors for physical layer functions will create more complete digital twins. Big data, that is not following the standard language used in information system but comes for example in forms of voice or image will first be processed in sensory organ information units from where they further will be delivered to the digital twin once recoded to standard language.

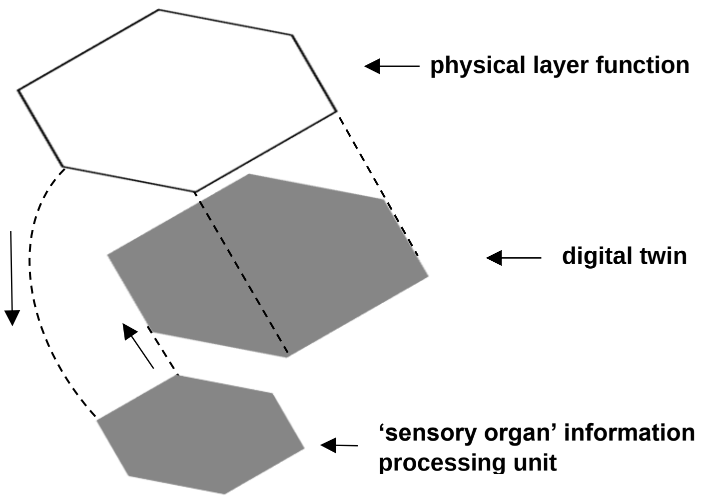

Figure 9: Data recoding through 'sensory organ' information processing unit

Another part of the sensory system is a specific sensory organ. Moller (2003, 3) explains how the development of sensory systems and sensory organs is an evolutionary adaptation of the vertebrates for the need to discriminate different stimuli. The emergence of big data has set similar evolutionary pressure to organizations. The multi-structural nature of big data covers potential and, developing mechanisms for extracting the potential increase the possibilities to survive the competition in 'survival-of-the-fittest'. Thus, the architecture model proposes applying information processing units that imitate sensory organs for analyzing big data that is not in a standard form used in the information system of the profit-organization. Sensory organs are based on such AI-technology as computer vision for image processing that can perform image analysis (Patrício et al. 2018, 71) or voice recognition. Data, that is not structured into a standard language of the information system of the profit-organization, will first be filtered through the 'sensory organ' information processing unit, before embedded to complete the digital twin.

Figure 9 shows an illustration, how the unstructured data is recoded to a standard language through 'sensory organ' processing. For instance, if big data is in a form of a photo, it will be first sent to the computer vision -based AI-application for image analysis and, after recoding the data into a standard language used in a information system, it will be further delivered to digital twin.

6.3.5. Control center for internal stability analysis

The architecture model proposes the inclusion of an information processing unit that acts as a control center of the system. Functions responsible for maintaining the stability of internal milieu in human body are controlled by the brain (Moller, 2003, 2). The control center information processing unit proposed in this model, analogically serves as 'a brain of the organization'. Figure 10 illustrates how the control center is connected to the physical functions of the organization through digital twins formed by data the receptors collect. Each digital twin has an interconnection to the control center and with the data delivered through the connections, the control center draws analysis from the internal stability of organization system. As the human brain possess higher cognitive functions, the control center similarly incorporates advanced analytics methods based on such higher functions such as machine learning algorithms. Intelligent machines, in this case an intelligent information system, are dependent on knowledge for sustaining their functionalities and, which ML is able to provide by learning from data identify patterns for the purposes to react to the environment (Alloghani, Al-Jumeily, Hussain & Aljaaf, 2020, 4).

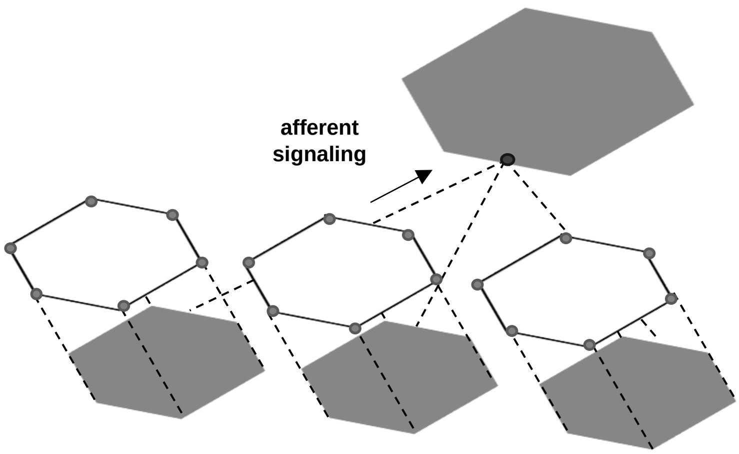

Figure 10: Placement of control center

6.3.6. Effectors for corrective actions

Effectors in human body are organs, glands, muscles (Marshall et al. 2017, 101). Svenaeus (2010, 179, 195) has examined organs from phenomenological perspective through and, emphasizes their place as a part and a belonging of a totality and, functional nature of them: *‘Organs make us able or, or not able, to do things, but they do not act themselves, they perform functions.’* Similar analogy can be identified in an organization system. The functions of the organization are analogically as organs. Effectors are included to the model to produce a correct respond to the stimulus (Marshall et al. 2017,) that may disrupt internal stability. Automatization for the effectors is received through the placement of actuators, that are acting nodes for process automation and control, that are able to act autonomously based on sensory signal received from physical world (Raza, Faheem & Guenes, 2019, 5). In this case, a sensory signal is data received from digital twins that are the basis of physical functions, in other words the physical world. The signal is sent to the central information processing unit, which exerts a command for corrective action if needed. This command is a activates the actuator for corrective action.

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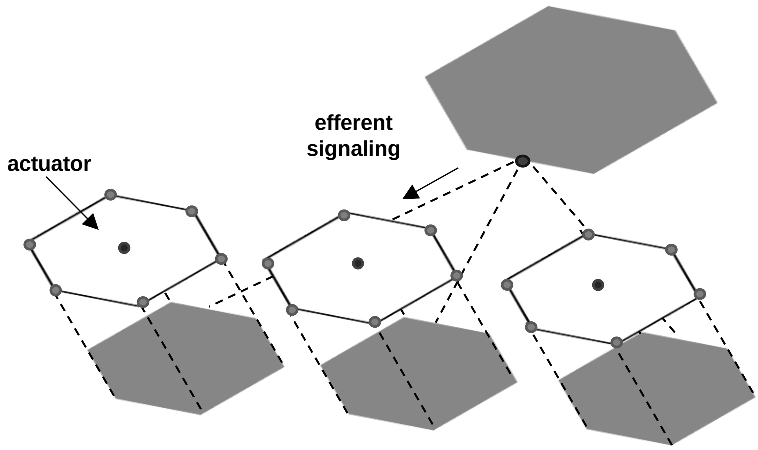

Figure 11: Placement of effectors

6.3.7. Autonomic nervous system for integrative communication

Final part of the architecture model is neural network that enables communication between the other elements required for homeodynamic process. Analogous counterpart in Industry 4.0's development for the network is IoT-interconnections. Autonomic nervous system enables afferent signal communication between the receptors and control center and, efferent signal communication from the control center to effectors. The IoT-connections between digital twins represent the autonomic nervous system. 'Sensory system' IoT-connections are links between digital twins and sensors of physical layer functions and 'somatomotor system' IoT-connections between digital twins and actuators of physical layer functions.

6.3.8. Final solution: architecture proposal and design framework

The solution transfer steps are summarized in table 2 in comparison with the components of homeodynamic regulation system in human body. Together they form an architecture proposal for intelligent cyber-physical system. The composition of the architecture is guided by the elements and organization of homeodynamic regulation process in human body.

Table 2: The comparison of biological parts and technical elements

Part in homeodynamic regulation system	Part in artificial intelligent system
Receptors, sensory system: sensors and sensory organs	Sensors for physical layer functions, ‘sensory organ’ information processing units with AI-applications that imitate human sensing (computer vision, voice recognition)
Effectors	Physical layer functions and digital twins, automated functionality with actuators
Control center, the brain	Central information processing unit, covers AI-algorithms that imitate higher cognitive functions such as ML-algorithms
Autonomic nervous system	IoT-connections between digital twins and central information processing unit
Sensory nervous system	IoT-connections between physical layer sensors and digital twins
Somatomotor system	IoT-connections between physical layer actuators and digital twins

The architecture requires a physical layer function map as its base. Cyber-counterparts of the digital functions are constructed first by using the existing data and data flows if any is continuously monitored. Digital shadows are complemented with physical function sensory placement and then connected to digital shadows for their completion into digital twins. As well, the architecture proposes ‘sensory organ’ information unit placement for analyzing non-structured data. A central information processing unit to operate as a control center, that receives information as afferent signals from digital twins delivered to them via sensors in physical layer. Actuators are placed to the physical layer for the automatization and, based on the analysis a control center draws from receptor signals, it exerts commands as efferent communication to digital twins that activates the actuators’ automatized effect. The communication between receptors and digital twins, actuators and digital twins and, digital twins and a control center is enabled with IoT-connection placement. These steps are summarized as a framework in figure 12 that can be utilized by for-profit organizations to facilitate in intelligent systems design process.

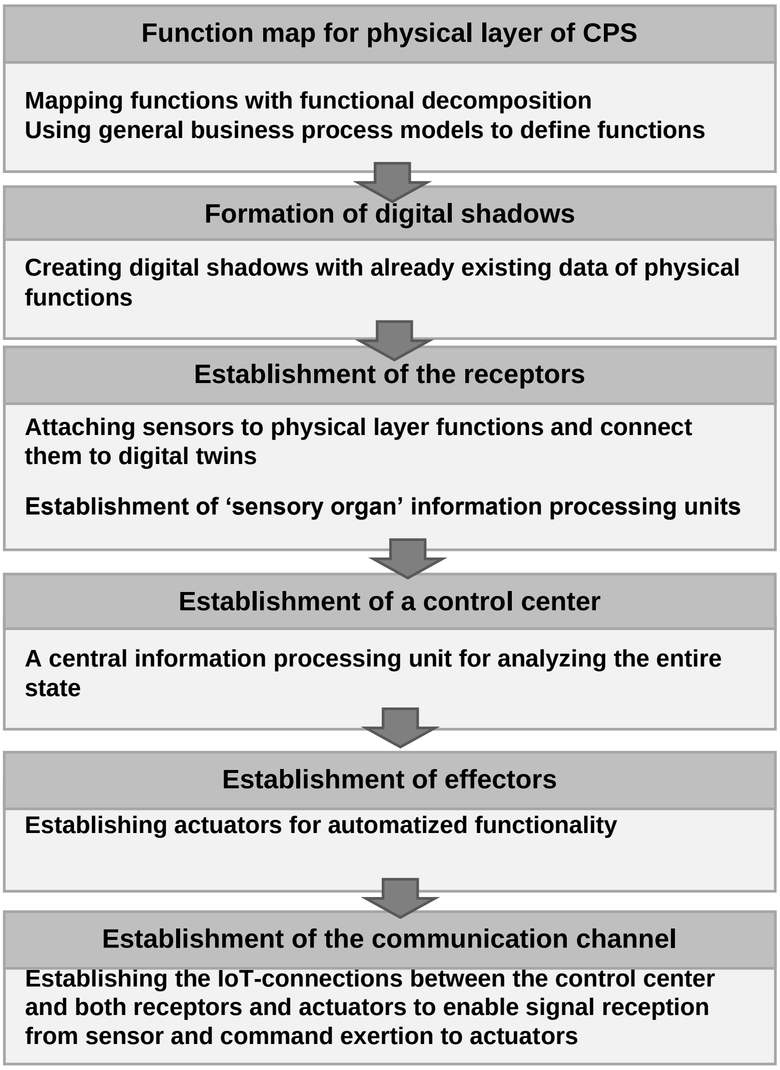

Figure 12: Framework for intelligent systems design

6.4. Evaluation

The analogy match between the human nervous system and technology development of Industry 4.0 was identified. The modeling of human nervous system was approached through homeodynamic regulation process in which, it has a central role for. Homeodynamic regulation process is for the maintenance of internal stability and, often appeared characteristic expected from Industry 4.0's intelligent system development is the capability to analyze and respond the environmental changes. Homeodynamic regulation process for the very same purpose. The analogical counterparts that enable internal stability maintenance were identified from the technology development of Industry 4.0. (see table 2).

The model is proposed is flexible and can be generally used for different types of for-profit organizations. The scope of can be expanded or narrowed as well. The model places a great emphasis for the formation of digital twins, suggesting that each physical layer function should have a complete digital twin on the cyber layer of CPS. The formation of complete digital twins for physical layer functions would improve the integration of CPS's physical and digital layers by making them more identical with each other. The completion of digital twins is enabled with receptor activity, including sensory placement for physical layer functions and AI-based 'sensory organs' establishment. Analyzing the incompleteness level of digital twins will reveal information gaps by addressing what kind of data is needed for more complete twin and, thus, facilitates data management for addressing the data acquisition and filtering, as well as, facilitating the connection establishment for better integration through guiding the sensory placement. Intelligent data classification and clustering improves as digital twins contain automatically clustered data. Sensory organ placement will facilitate the AI-application and, their proposed use as filters for data that is not in standard form for what is used in an information system gives a solution for dealing with multi-structural big data.

The model suggests establishing a control center connected to each digital twin. Control center includes ML-algorithms and other algorithms that imitate higher human cognitive functions but are still improved with certain terms such as computation capability. Control center receives information from the state of each digital twin and combining this data it draws analytics from the entire state of a profit organization system for maintaining internal stability of it.

7. DISCUSSION

7.1. Results and conclusions

Industry 4.0 is progressing rapidly, re-organizing our current systems and infrastructures which is expected to have a transformative effect to our lives (Cukier et al. 2013; 39; Jagadish et al. 2014, 86; Jin et al. 2015, 59 Griffiths et al. 2018, 29). On the other hand, the transformation requires new ways to think (Griffiths et al. 2018, Cochrane, 2019). Intelligence seems to be a desired quality and in the vision of Industry 4.0, and it is assumed to express itself in many advancing ways such as self-organizing capabilities and capability to react to the environment and solve complex problems. For for-profit organizations, adapting to the changes of Industry 4.0 is important both to maintain competitiveness (Kotler et al., 2010, 12, 44) and to forward the overall sustainable development (Cochrane et al. 2019). The objective of this study was to attempt to complement computational AI of intelligent systems of for-profit organizations by extending the mimicry of intelligence to a physical layer of the system

The main research question RQ1 of the study was as follows: ‘How to design an intelligent cyber-physical system for a for-profit organization?’. To forward the main question, the sub-research question RQ2 ‘What are the intelligence attributes of a cyber-physical system?’ was set to guide the investigation of how what the intelligence is in the context of Industry 4.0. Overall, intelligence is a general desired attribute, that arises frequently in the Industry 4.0 related literature It is expected to give certain characteristics that help with prediction, complex problem solving and reacting to environmental changes. It is a general factor that leads to value creation. In cyber-level, intelligence is related to AI applications as well as cognitive qualities of big data. In physical level, it is related to physical IoT-interconnection. The concept of CPS merges both elements.

The study adaptively adopted biomimetic design process stages defined by Cohen et al. (2016, 21-25), to follow a similar path as with the as in current AI-study, that is, the imitation natural intelligence. To consider the target under re-design sub-research question RQ3 ‘How organizational design should be approached?’ was set. STS design model approaches organizational design with a perspective that considers the interplay of social and technical sides of the organizations. The importance of considering systemicity was arisen, both due to the complex and systemic nature of the organizations and the development of Industry 4.0 that is leading towards the more systemic world. STS-design model is deliberately influenced by systems theory and, thus, allows taking these perspectives into consideration.

New design process framework was constructed for the purposes of this study by embedding the elements of biomimetic design process with the classic STS design framework presented by Winby et al. (2018). The analysis considering the development of Industry 4.0, as well as the analysis of how it affects profit-organizations were a basis for the formation of the problem statement of the study. Design process proceeded further to the identification of an analogy source of a biological system that incorporates natural intelligence.

Human cognition presented analogical similarities with artificial information processing needed when managing big data, for which it was further selected for abstraction. The focus was shifted on physical structures from the cognition. Getting familiarized with the basic mechanisms, processes and structures of human cognition through literature related to human nervous system and Artificial Neural Networks revealed, that human nervous system possesses other mechanisms that could improve the overall information system to the same direction Industry 4.0’s development is leading to, which expanded the scope of the analogy source just from human cognition to the entire human nervous system. Human nervous system has a central role in a homeodynamic regulation that enables maintaining relatively stable state in human body despite of internal and external disruptions. The elements of homeodynamic regulative system, that are, receptors, effectors, a control center and a communication center were abstracted into function principles for further technical transfer.

In solution concretion step of the design process, it was concluded that biomimetics can be applied in system design for profit-organizations to enhance their value creation by improving their adaption to Industry 4.0's development. Concretizing the abstracted principles of the parts that are required for homeodynamic regulation revealed, that key technology concepts in Industry 4.0's development are analogically similar to some of the biological parts. Homeodynamic regulative process served as a framework with the placement of the technology concepts and, some additions were suggested to complete the re-designed architecture to resemble the structure needed for homeodynamic regulation.

The design process that was based on biomimetics produced a novel way to approach the development of Industry 4.0. It resulted a neural network -based framework for intelligent systems design for for-profit organizations. It expands the concept of AI to the physical layer of CPS by mimicking the components and the organization of homeodynamic regulation process, creating an ideal environment for the AI-algorithms to operate and encourage the cognitive capabilities of big data.

7.2. Practical implications

An architecture proposal for an intelligent cyber-physical system for for-profit organizations was constructed as a result of the design process of this study. As well, a framework to facilitate the intelligent cyber-physical system design process was derived from the architecture. The architecture aggregates the key technology concepts of Industry 4.0 into one model through the analogy of homeodynamic regulation system. The framework provides a systematic and logical tool to guide the design process of intelligent systems.

The tool and the proposed architecture are flexible in terms of context and scope of the design. As the architecture is based on functional mapping and functionality it universal, the model can be used regardless of any specific attributes of a for-profit organization. Functionality based mapping allows using the model in the context of other types socio-technical systems, albeit the baseline for functional mapping, that is business modeling in this study, needs to be reconsidered in this case. As well, the function mapping technique proposed is general in terms of the context and the scope of the modeled system. It allows narrowing the scope to smaller functional entireties within an organization for more detailed analysis and expanding the scope of the examination for outside the intra-organizational system boundaries to chart the environmental factors affecting the system.

7.3. Theoretical implications

The approach of this study was a design research, that combines the use of scientific knowledge with the design process. As design research emerged from the recognition of intuitive design methods being not sufficient for complex industrial design in modern era (Cross,1993, 19), it was as an approach ideal for examining Industry 4.0 and its design needs. The research process was not linear but, rather, a discourse between the theory examination and the design, which helped to form a more concrete picture about the current problems in theory of Industry 4.0 and the practical needs of the design. During the design process, the attention became directed towards ‘intelligence’ as a frequently mentioned desired quality, and, due to its frequency in the literature, it became a general term for this study to describe the development of Industry 4.0. This is aligned with Lugmayr’s et al. (2017, 198) statement that examining big data needs more epistemological view instead of the dominant technical perspective. The same point about shifting the perspective away from technical is valid to cover the overall development of Industry 4.0, if the goal is generalized under non-technical concept intelligence.

As well, design research is advantageous method for closing the gaps in theory behind design, as such closure is needed to meet the practical demands of the design (Edelson, 2002, 118). The study attempts to close the gap between the theory and the on-going design and development of Industry 4.0, by arguing for the concept of AI and the mimicry process related to it should be expanded to cover intelligent design more comprehensively than just computation, to where it is currently mostly focused on. Similar arguments have been presented for example by Kujala et al. (2018) and Howard et al. (2019). During the analogy source identification step of the design process, analogical similarity between the Industry 4.0’s intelligent systems design and human nervous system was identified. Industry 4.0’s technological concepts had analogous match with the components and (see table 2), as well the desired characteristic or even a requirement for for-profit organizations (Kotler et al., 2010, 12, 44, Dalpiaz, Giorgini et al. 2013, 2) and visioned intelligent systems in general (Kujala et al. 2018, 8; Alloghani et al., 2020, 4) is quick reactivity to environmental changes.

The analogy match is centered upon the homeodynamic regulation system of human body that consists of certain elements and, that has a purpose of maintain the internal stability (Jänig, 2006, 1; Marshall et al. 2017, 9-10). Helmold (2019, 162) defines an intelligent agent as a device that has an ability to perceive its environment and takes actions for maximizing the changes to achieve the goal. Homeodynamic regulation system and, followingly, the proposed architecture that is based on it, can be said to be an intelligent agent after this definition. More detailed is explained in the following, how the adoption of the architecture would add intelligence and value creation through the added intelligence from both technical and social perspective.

7.3.1. Technical perspective

The suggested architecture proposal extends the concept of AI to a physical layer of CPS through homeodynamic regulation process in human body. The architecture improves the integration goals of Industry 4.0. The architecture merges physical and cyber layers of CPS through physical function – digital twin match. It ties together the main functional components of CPS and the enabled functionality as described by Lee et al. (2015, 19): it enables a two-directional data flow between data acquisition from physical layers through receptor components and information feedback from digital layer through efferent signals from the control center.

The architecture addresses IoT-connection placement and quality and suggests establishing them between two types of information processing units: digital twins and a control center. Connection types are sensors-digital twins for receptors to monitor the activity, actuators-digital twins for effectors to automatize the activity, and digital twins-control center for a neural network-based communication channel for integrated communication. The interconnection and information processing units support the idea of integrated CPS with the core that is based computing and communicating, that is monitoring, coordinating, controlling and integrating the entire systems (Rajkumar et al. 2010, 631). Receptor connections monitor, a control center coordinates and controls and, the communication channel is integrative. The architecture supports decentralized information processing through separate information units for parallel processing information.

The architecture based on homeodynamic regulation system gives a general reason for a big data to be acquired, curated and analyzed, that is, to maintain internal stability of the organization. With this general reason, it enhances extraction of cognitive capabilities of big data. Analyzing the incompleteness level of digital twins will reveal information gaps by addressing what kind of data is needed for more complete twin and, thus, facilitates data management for addressing the data acquisition as well as filtering. Digital twins cluster data, sensory organ information unit placement will facilitate the AI-application and, their proposed use as filters for data that is not in standard form for what is used in an information system gives a solution for dealing with multi-structural big data. Thus the architecture provides a solution for some current data management issues (Jagadish, et al. 2014; Braun, Kuljalin & DeShon, 2018)

7.3.2. Social perspective

From social perspective, the model allows new knowledge creation that can be turned into strategic competency. Bettiol et al. (2020, 7) pointed out Industry 4.0’s integrative environments and the following integration of big data and ERP-activity may generate new knowledge about the processes and improve organizational learning. The architecture proposal generates knowledge by consisting digital twins that represent physical layer functions as complete as possible. The completion process of them includes new data extraction. Both extracting new data for digital twins and digital twins themselves generate new knowledge. Extraction closes the information gaps and digital twins provide an information image of physical layer function. Establishing a control center information processing unit that analyzes the entire state of the organization will as well generate new knowledge, and improve systems understanding. Digital twins analysis helps with understanding how the organization operates as a system. Once this knowledge is internalized within the personnel of the organization, it may improve intuitive responsivity to the changes and disturbances that are meaningful and might impact to the operation of the organization, through growing systems understanding. Knowledge itself can be turned into customization and optimization.

If the physical function mapping is approached with alternating homo economicus paradigm, it can influence the modeling process and help with designing the model that embraces sustainable development. New ways of thinking as beginning point for sustainability (Cochrane et al. 2019,). Ferraro et al. (2013, 129) present *homo faber* as an alternative for *homo economicus,* an ideology that embraces making instead of doing and says its potential in helping to '*loosen the grip of the relentless pursuit of productivity'* that is one of the key reasons. Physical layer mapping can be doubled learning process fueling the sustainable development. Construction process that combines both, a shift guiding thinking and the construction itself, functional mapping, teaching more about systemicity. As one the one hand, this era is changing our mindsets and, on the other mindset change is needed to keep going. New way of thinking as beginning point for sustainability (Cochrane et al. 2019,).

Popkova et al. (2020, 566, 578) emphasizes that human and artificial intelligence will be equally important, and they will be used together. The architecture proposal, together with approaching design from the alternative view to *homo economicus* will embrace this kind of human-machine symbiosis, in where humans and machines are allocated to tasks suitable for them. Homo faber, suggested by (Ferraro et al. 2013, 129) has an emphasis on making instead of producing for humans, and they state that the adoption of the ideology may also bring new working opportunities (Ferraro et al. 2013, 129). Balsmeier et al. (2019, 9) state, that the adoption of digital technology has an impact on job descriptions by increasing the demand of high-skilled and decreasing low-skilled work. They also noted that, even though the total net effect of the employment is positive, temporary unemployment rate among low-skilled workers may increase and, that the development and application of the methods that supports this to adapt the current labor distribution to the changes is an important investment. Levine et al. (2015) points out the efficiency and creativity hidden in heuristic, cognitive short-cut processes humans have a tendency to: it is an effective way to deal with complexity with biological limitations and connected to analogical reasoning, which is seen as a fundamental source of creativity. Industry 4.0 allocates humans for more creative tasks and automatize monotonous tasks. By challenging *homo economicus* and adopting ideas from *homo faber* can facilitate this process.

7.4. Limitations of the study

The results of this study should be considered against of the potential limitations they come along with. First, the results that concern the establishment of the architecture are theoretical. Both Cohen et al.'s (2016, 21-25) biomimetic design process framework and Winby et al.'s (2018, 403) STS-design process model suggested coupling the evaluation of the final solution with iterative testing in order address the possible issues of the solution and correct them for further improvement. This study, however, does not include iterative empirical testing of the architecture which leaves the results of the architecture's practical applicability to remain theoretical and, thus, affects their validity and reliability. The proposed architecture also remains still quite abstract as an applicable solution from technical perspective. The architecture proposal is predominantly directional as is. More specific technical knowledge is needed to develop more concrete solution.

Some limitations of the study are related of the architecture proposal's usability and value creation realization for for-profit organizations. Whereas, on the one hand, the generality of the proposed design framework is an advantage, it also becomes a limitation of the model, on the other hand. It only provides broad guidelines for the architecture design. As well, as the empirical testing of the model remains, there are no estimations of potential investments for what it takes to design the proposed architecture. Reconstructing the organization's information system architecture to follow the proposal may cause negative effects on business performance in shorter run.

7.5. Future research opportunities

The first future research opportunities arise from the limitations of this study. Empirical testing of the architecture proposal would provide information of its practical validity. Simulation test could work as a suitable preliminary testing method, giving guidance and direction of the validity and address the possible problems of the proposal. Empirical testing in case organization environments would, however, give more valid results. Empirical testing would help with addressing the gap between the current architecture systems and the proposal, albeit it is context-specific as organizational information system solutions vary greatly.

During the biomimetic design process and its analogy source identification, along with the human nervous system, another potential biological phenomenon was identified for mimicry for added intelligence. Evolution itself could provide principles for self-adaptation for maintaining internal stability in a long run in a changing environment. Evolution has been under interest in optimization and problem solving for decades since evolutionary computation started to emerge (Whitley, 1993; De Jong, 2009; Bäck, Hammel & Schwefel, 1997, 4). It has produced many successful applications in varying fields and, as well has been effective in optimizing neural network architectures in computation. There is an initiative idea of bringing evolutionary principles into physical system design and followingly, concepts like evolution-of-things (Eiben, Kernebach & Haasdijk 2014; Howard et al. 2019) have emerged. Applying mechanisms that imitate with evolutionary principles to the neural network-based information system architecture could bring the self-organizational attributes to the model and for example improve the automatic reactivity to the environmental changes the organization might be influenced by. Adding analysis layer to the model with evolutionary mechanisms to analyze changes in environmental conditions and suggest 'mutations', in other words, predict and suggest the change requirements that are needed for the organization system to improve its efficiency in its operation environment.

The architecture proposed to support intelligence in this study suggests establishing a control center that facilitates the homeodynamic process for the maintenance of internal stability. In human body, brain is the control center for general homeodynamic regulation. Similarly, the control center information processing unit needs to incorporate advanced analytics methods that can analyze the data and entire system for the maintenance of internal stability. Current ML-algorithms are ideal for this purpose (Alloghani et al., 2020) but, to get more advanced central information unit functioning that produces more detailed analytics, the control center could incorporate algorithms, that imitate higher cognitive processes, in a larger scale. In imitation, however, biological limits of human cognition that are present for example as heuristic cognitive short-cut processes (Levine et al. 2015), should be considered. As machine intelligence has proven to be effective in complex problem solving and analyze vast amounts of data, in which human cognition has limitations, the exact imitation of human information processing is not necessarily the way to produce suitable methods for machine intelligence but, instead, paying attention for general analogies behind the mechanisms.

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