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Patented Intelligence: Cloning Human Decision Models for Industry 4.0

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Abstract. Industry 4.0 is a trend related to smart factories, which are cyber-physical spaces populated and controlled by the collective intelligence for the autonomous and highly flexible manufacturing purposes. Artificial Intelligence (AI) embedded into various planning, production, and management processes in Industry 4.0 must take the initiative and responsibility for making necessary real-time decisions in many cases. In this paper, we suggest the Pi-Mind technology as a compromise between completely human-expert-driven decision-making and AI-driven decision-making. Pi-Mind enables capturing, cloning and patenting essential parameters of the decision models from a particular human expert making these models transparent, proactive and capable of autonomic and fast decision-making simultaneously in many places. The technology facilitates the human impact (due to ubiquitous presence) in smart manufacturing processes and enables human-AI shared responsibility for the consequences of the decisions made. It also benefits from capturing and utilization of the traditionally human creative cognitive capabilities (sometimes intuitive and emotional), which in many cases outperform the rational decision-making. Pi-Mind technology is a set of models, techniques, and tools built on principles of value-based biased decision-making and creative cognitive computing to augment the axioms of decision rationality in industry.

Keywords: Industry 4.0, Pi-Mind, Decision-Making, Cyber-Physical System, Cognitive Models, Collective Intelligence, Value System, Preference, Clone, Patented Intelligence, Smart Decision, Ontology

1. Introduction

Industrial automation, if understood simply as an integration of software components, electronics and mechanical devices on the factory floor, is not anymore giving companies any competitive advantage or industrial leadership. The tendency towards automation was established more than a half-century ago and since then it has managed to become a reality for the whole industry. A number of IT solutions for high-tech industrial production, which have been developed, introduced and standardized, were gathered under the concept of the Third Industrial Revolution and considered to be a history now. The current phase of the industrial development is shaped by the features of the so-called Fourth Industrial Revolution or Industry 4.0. According to the definitions of one of its ideologists, *it is characterized by a fusion of technologies that is blurring the lines between the physical, digital, and biological spheres* [1]. The era of the Industry 4.0 does not bring new technological solutions or the evolution of the old ones; it offers a principally new vision on how the company should operate: manufacture products, provide services, manage assets and do business in general [2,3]. The main design principles of the Industry 4.0 are: interoperability of all its components (machines, devices, sensors, software, data, people, etc.); virtualization of the physical world; decentralization of control and decision-making; real-time capability; use of service-oriented architectures; and modularity of the systems [4].

The leading consulting groups report that many industrial and service-oriented sectors are facing strong barriers set by the new non-trivial tasks appeared in the period of transferring to the technologies 4.0 [5,6]. The main implementation barriers are related to coordination of actions across different organizational units, cybersecurity issues, data ownership when working with third-party providers, lack of workers' courage and necessary talents [6]. Companies fail to ensure sufficient digital culture and are not capable of creating a vision of the future.

The success of the transformational processes, within the increased uncertainty and system resistance context, is strongly dependent on the expertise of individual employees, *change agents*, who are introducing new business models, launching smart processes, developing smart products and providing assistance and guidance to others. To widely deploy Industry 4.0 solutions, companies need quite many skillful change agents. This is especially critical for a successful decision-making. Wide adoption and understanding of the new decision-making models and practices require continuous organizational learning, experience transfer and benchmarking.

While the routine and physically demanding jobs have become robotized almost completely, a creative, strategic or emergent decision-making is still a human-dominated sphere today. However, the rise of the Internet-of-Everything and emerging advances in AI (particularly, in Deep Learning) is rapidly changing such human dominance. Artificial decision-makers and problem solvers are capable of providing more accurate and fast decisions and they will replace many of human employees. Artificial agents, which are installed in various planning, production, and management processes, can take the initiative and responsibility of making decisions throughout the whole factory life-cycle and implement the Intelligence-as-a-Service paradigm for the real-time automated decentralized decision-making. This brings up an issue of the artificial decision makers' learning and benchmarking.

Current technologies are focused mainly on the normative models emphasizing the rational aspects of decision-making. Though the creative cognitive capabilities of an agent's behavior are as important as the features of the environment, in which this behavior takes place. New models of judgment and decision-making must follow the principles of cognition to augment the axioms of decision rationality.

In our research, we focus on the models capable of capturing cognitive aspects of creative human decision-making based on personal values and preferences and their application in industrial cyber-physical systems. We create a mechanism of cloning humans' decision models aiming to approach automatic decision-making but still keeping a human in the loop (Collective-Intelligence-as-a-Service). We aim to answer: how to digitize, evaluate, appreciate, share and reuse expert decision-making skills and experience; how to embed cognitive aspects of decision-making and problem solving into the existing schemes of the industrial operation; how to create an infrastructure around a digital pool of best industrial practices; how to enhance human-machine collaboration; how to make decisions on the basis of self-awareness.

2. Related Work

Creation of intelligent physical and software-based systems, which are programmed to learn and adapt, is among the top strategic technology trends announced in the latest analytical reports [5, 6]. Interaction of people, devices, content, and services, sometimes called Intelligent Digital Mesh [7], has evident effect on transformations across industries and fields: the virtual and physical worlds are becoming more intertwined due to new bridging technologies enabling advanced communication and interaction of diverse intelligent objects, both human beings and machines.

New possibilities for manufacturing environment are promising. The biggest challenges here are continuously changing markets with growing demand for customized and complex products, on the one hand, and organization of the production in a competitive, competent and sustainable way, on the other one [8]. The solution is foreseen in the next generation of industrial automation systems capable of the autonomous control, forecasting and streamlined planning, smart multi-objective optimization, dynamic and adaptive reconfiguration of the manufacturing and logistic structures, customized production, cognitive behavior, advanced analytics and on-the-fly complex decision-making. In order to meet these requirements, the automation systems are implemented as cyber-physical systems (CPS). They integrate computing systems and physical counterparts, such as sensors and mechatronic components, into a network structure [9]. Communication between elements within a CPS and exchange data with information systems and other CPSs is performed via some data infrastructure, e.g., the Internet, leveraging on the Internet of Things technologies. The ability to interact with other CPSs and humans is a key enabler of future technologies and a paradigm shift towards Industry 4.0 (see Table 1) and smart factories, also called factories of the future [2,10,11].

A smart factory is an ecosystem including heterogeneous systems, processes and diverse actors, which are distributed, autonomous, intelligent, proactive, fault-tolerant and reusable by their nature. The old structure of industrial systems has been traditionally described in terms of the 5-level hierarchical model [12] by utilizing standard enterprise architectures performing, e.g., SCADA, DCS, and MES functions. With the growing popularity of service-oriented architectures, a factory is being transformed into a horizontal architecture represented by "a cloud of services", where the functionalities of each cyber system or physical device can be offered as one or several services, hosted in the cloud [2].

Table 1. Comparison of the key concepts from the paradigms of Industry 3.0 and Industry 4.0

Industrial system features	Industry 3.0	Industry 4.0
1. Architecture	Hierarchical architectures	Clouds of services
2. Processes construction	Waterfall-based	Agile factory
3. Automation trend	Automation	Virtualization
4. Operations and actions support	5-layer automation pyramid (ERP systems, MES systems, SCADA systems, PLC and DCS systems and the actual input/output signals)	Advanced manufacturing (Additive manufacturing, advanced materials, smart, automated machines), IoT, CPS, Big Data, Cognitive technologies and Artificial Intelligence
5. Type of interactions	Worker – function	User – service
6. Organization of the technological process	A rigidly defined sequence of closed interaction between specialists	Collaborative interaction in cross-functional teams
7. Decision-making	Person (worker) or automatic systems	Human decision makers, smart agents and cyber-physical systems

The actively debated open issues are as follows: what would be the role of a human in a smart factory; how the responsibilities and duties should be distributed between humans and machines and how their interaction should be organized throughout all phases of a factory life cycle. The vision of a smart factory varies according to the level of human engagement into its operation.

A CPS can be one of the following:

- Fully autonomous, i.e., acts independently of humans.
- Triggered by human inputs.
- Dependent on a close interaction with humans, including a shared control [13]. Such systems are called human or human-in-the-loop cyber-physical systems (HCPS) and include also a necessary loop involving a human in addition to the cyber component and the physical environment [14].

HCPS imply that human employees have greater freedom to make their own decisions, become more actively engaged into creative design and planning processes as well as into the operational working environment and they are able to regulate their own workload. Humans, in this case, are the central component of the factory ecosystem. They are empowered by the comprehensive assistance of smart machines with multimodal, user-friendly interfaces. Romero et al. [15] emphasize on a human-centricity of the smart factories' deploying systems, which enhance the cooperation of machines with humans. Such human-automation symbiosis and appropriate human-centered architecture for the next generation balanced automation systems has been reported in [16]. Kagermann et al. [10] argue that increase of human involvement is closely related to the social responsibility. A variety of interaction types increases due to the emerging socio-technical interaction models and advanced communication technologies. Application of intelligent agent-based architectures, robotics and alternative interfaces between humans and the cyber-physical environment makes such interactions smart, cooperative and self-managed. In Schirner [14], for instance, it is shown how the new brain-computer interfaces (BCIs) and controlled assistive robots can be integrated into HCPS to restore a fundamental autonomy for people who are functionally disabled due to various neurological or physical reasons. All components of CPS, both computational and physical ones, are becoming autonomous, capable of control and response to different situations, self-configuring, knowledge-based, and spatially dispersed [10].

The technological advances allow creating smart industrial robots, which are the main driving force of Industry 4.0 [17]. New collaborative robots, such as the Kuka LWR [18] and the Universal Robot UR [19], have been deployed in factories to provide complementary skills to human co-workers.

Collaborative robots (or cobots) are capable of human-robot collaboration (HRC) and work hand in hand with their human colleagues on the factory floor for manufacturing in real-world settings. The vision of collaborative robots' role has changed since early understanding of the cobot concept as *an intrinsically passive robotic device, which provides assistance to the human operator by setting up virtual surfaces, which can be used to constrain and guide motion* [20], to today's *intelligent machine with cognitive and sensitive capabilities* [21].

The early cobots were highly task-oriented and very specific in their functioning. Today's trend is to create more universal entities to be used for a wide range of manufacturing processes. The robots are developed with a very small initial number of own skills and capabilities, but they are designed with advanced abilities to learn (from humans, the environment, other robots, etc.) and to access all kinds of needed decentralized data in networks or in the cloud of services, in which they operate. Such vision, on the one hand, enables implementation of the "Robotics-as-a-Service" paradigm; on the other hand, it emphasizes the role of the hybrid collaborative environment, in which robots learn how to operate.

Collective intelligence, emergent from the collaboration, competition, and cooperation of many natural and artificial individuals, is a valuable asset of the industry and a powerful enabler of smart decision-making throughout diverse organizational and manufacturing processes. It addresses the problem of multiple views' integration regarding some problem shared within a large group of individuals and provides models for the collective decision-making. Coordination of peers is quite complicated within such models because of the decentralized network structure. Swarm robotics is an approach to perform this coordination efficiently. It is built on top of the idea that the behavior of a large number of robots is in a way similar to the self-organized behavior of social animals grouped in swarms (ants, bees, birds' flocks, etc.). The principles of collective (swarm) intelligence can be applied to robotics [22]. Integration of smart, networked sensors and actuators into a connected world of robotic swarms is greatly appreciated in industry [23]. New data structures, learning models for processing collective behavior in open systems and swarm algorithms for revealing hidden behavioral patterns, which can be used for prediction and decision-making, are developed for various purposes such as search for an optimal solution [24].

Along with the robot-robot type of interaction, human-robot collaboration plays a critical role in safety, productivity and flexibility of the manufacturing. Research in the field of cognitive robots, which share space and tasks with humans, has shown the importance of the robot's human-awareness [25]. In various industrial processes, a robot has to be equipped with an explicit reasoning tool focusing on the human as a potential collaborator. Alami [25] shows that it is critically important to make robots understand human models of behavior for successful human-robot collaboration and introduces a framework for human-robot interactive task achievement that is aimed to allow the robot not only to accomplish its tasks but also to collaborate with its human partners and to interpret human behaviors and intentions.

Although the lion's share of research in this field seems to be mainly focused on a physical human-robot interaction, such as human-aware navigation [26] and motion, we argue that cognitive aspects of HRC are of the highest importance too. Robots should understand and (in some contexts) reflect human cognitive behavior in learning, decision-making, reasoning, etc. Essential work has been done in the field of human-aware decision-making and human-like behavioral modeling by Lemaignan et al. [27]. Sadrfaridpour et al. [28] study trust modeling issues in human-robot collaborative manufacturing. Along with the collaborative capabilities, modern robots should acquire cognitive capabilities that are inspired by the cognitive processes of the human mind [29]. The ambitious goal would be to build a cognitive system implementing a human-like intellectual capacity to full extent: beginning from the ability to generate ideas and find problems up to the recognition and formulation of new tasks, self-assessment of own creativity and personal performance, which requires self-awareness and self-configuration from the system. Advances in Deep Learning are promising in this context [30].

3. Cloning Human Decision Models for Industry 4.0

3.1 Pi-Mind Technology

Our vision of a smart factory is based on a self-managed digitalized human expertise provided as smart service for various industrial decision-making processes. It is an ecosystem, which embeds cognitive aspects and biased decision-making into existing automated schemes of the operation. Appropriate communication and collaboration infrastructure is built around providers and consumers of successful industrial decisions (see Fig.1).

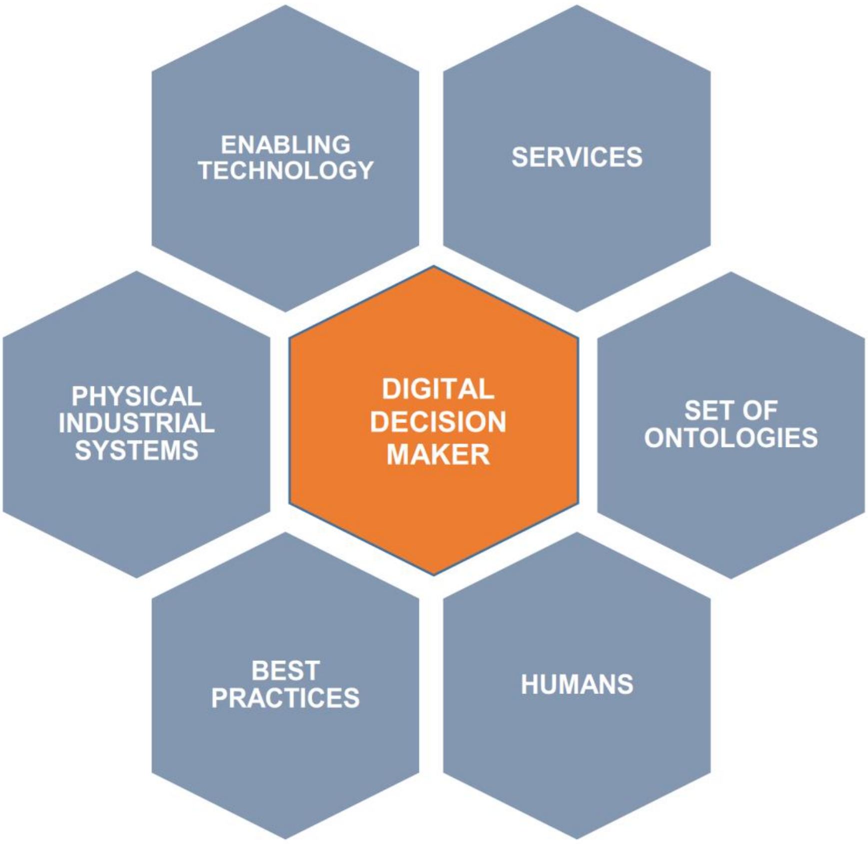

Figure 1. Pi-Mind-enabled ecosystem of a smart factory

The technology of Pi-Mind (Pi or π stands for "Patented Intelligence") is a set of techniques, models and tools aimed at digital twinning (or cloning) of a human decision-making behavior in such situations, which allow free choice of an alternative action based on the unique personal preferences. The technology also augments the traditional (for industrial context) rational decision-making models by incorporation of cognitive and creative aspects.

Patented Intelligence is a digital shared copy of a person's decision system based on his or her values and also a set of decision-making schemes used for specific tasks. The technology name comprises the word *patented*, which is correlated with the concepts of an intellectual property licensing, commercialization, reuse and exploitation. The word originates from the Latin *patere* and means *to stand open*, i.e., public. A patent of an invention is a set of rights acquired by an inventor in exchange to the invention's detailed disclosure; analogically, a "patent" on a decision model is a tool of assigning the ownership of a digital value system to the decision maker and to make this assignment public.

The technology can be applied to a variety of tasks and problem domains (see Fig.2).

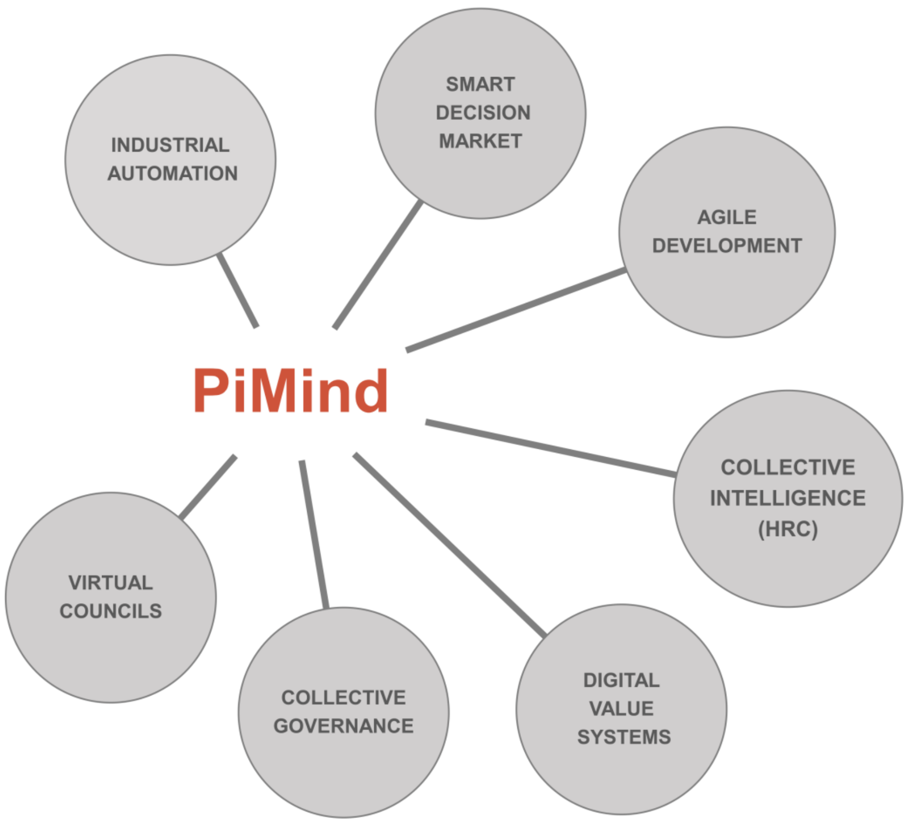

Figure 2. Application of the Pi-Mind technology

Making a decision means committing oneself to a course of actions where plausible alternatives exist for making possible choices. Studies show that human choices of alternatives are remarkably dependent on the combination of rational and creative thinking [31]. They emphasize the role of experience, the cognitive underpinnings, frames and biases, which enable a human to rapidly categorize situations and make effective decisions [32,33]. The needed scope of capabilities for a decision-maker (also a digital one) is determined by a combination of fundamentally different approaches:

- logical and analytical information processing, reasoning and inference based on rational thinking;
- intuitive prediction on the basis of abstract thinking and experience.

Decision-making is actualized in such conditions:

- there is a significant gap between the current and the desired situation;
- the ways to eliminate the gap are unknown;
- there is a person interested in narrowing this gap;
- the person has the means and authority to eliminate such a gap.

The gap between the current and the desired state is seen as a major challenge. The solution assumes narrowing the gap by choosing one (best) alternative from the set of available alternatives at each intermediate state. An alternative is chosen as a result of current state assessment using a set of criteria and available knowledge on each of the options. Each alternative defines a unique set of actions.

The formalization of the rational and intuitive decision behavior symbiosis uses semantic modeling approach and it is based on several ontologies (see Fig.3):

- *Upper Ontology* - Decision Ontology, providing basic means for describing decisions and decision-making (see, e.g., Rockwell et al. [34]);
- *Pi-Mind Specific Ontology* - Ontology of Values, describing a value-based model of decision-making;
- *Domain Ontologies* - a constantly growing set of ontologies describing the structure of decision scenarios for specific domains. The main domain ontology for Industry 4.0 is the Ontology of Manufacturing.

Key concepts of the decision-making are described in Table 2.

Table 2. Key concepts of the Pi-Mind Technology

Concept	Description	Ontology
Environment	Integrates the following interrelated elements: - CPS. - Production processes as controlled objects, their separate cycles, operations, etc. - Decision makers, decision models. - Tools available to the decision makers (machinery, sensors, devices, mechanical tools, information and communication systems, resources).	Ontology of Manufacturing
Environment State	A set of specific values of the environmental parameters that describe the environment at a given point of time (state of the ecosystem)	Ontology of Manufacturing
Situation	The state of CPS and the environment, in which it operates at a given point of time (state of the	Ontology of Manufacturing

	system)	
Problem	The state of the system, in which its parameters do not match the desired or required ones (a problem situation)	Ontology of Manufacturing Ontology of Decision-Making
Alternative	Type of a decision, a way to use tools available to a decision maker	Ontology of Manufacturing Ontology of Decision-Making
Set of Alternatives	All alternatives available for a decision maker, w.r.t. the available resources and authority level	Ontology of Manufacturing Ontology of Decision-Making
Goal	The state of the system in which all parameters match the desired or required ones from the point of view of a decision maker	Ontology of Manufacturing Ontology of Decision-Making
Set of Decision Patterns	A set of patterns for possible application of models and methods of decision-making within both rational and intuitive decision context	Ontology of Manufacturing Ontology of Decision-Making
Decision Model	Formal model of decision-making	Ontology of Decision-Making
Preference	Any form of ordering of the evaluated elements, elimination of uncertainty by making a choice	Ontology of Values
Criteria	A rule allowing to compare alternatives	Ontology of Values
Decision	Outcome of the decision process, state of the environment at the final point of decision-making process	Ontology of Values
Value System	A formalized system of preferences of a decision maker for various situations as a standard to guide his behavior in all situations, particularly in decision-making	Ontology of Values
Clone	A software agent as a keeper and a simulator of the personal value system(s) of its owner and as a representative of him/her at various decision-making situations	Base of Decision Makers

The novelty of the decision technology is in the two-layer decision model, which comprises the unified decision-making in terms of basic formal models, methods and the value-based customized decision-making based on personalized preferences of a decision maker. A decision maker's value system is formed as a result of the experience in industrial decision-making. Preferences of a decision maker are described with unique sets of parameters, criteria and their values in correspondence to each specific goal. The two layers of the model are integrated by application of personal preferences to a given decision model (e.g., any multi-criteria decision model, neural-based, fuzzy, rule-based, etc.). Preferences can be programmed explicitly by decision makers, or implicitly by machine learning. After a quantitative evaluation of possible alternatives is done, the best alternative will be chosen as a solution.

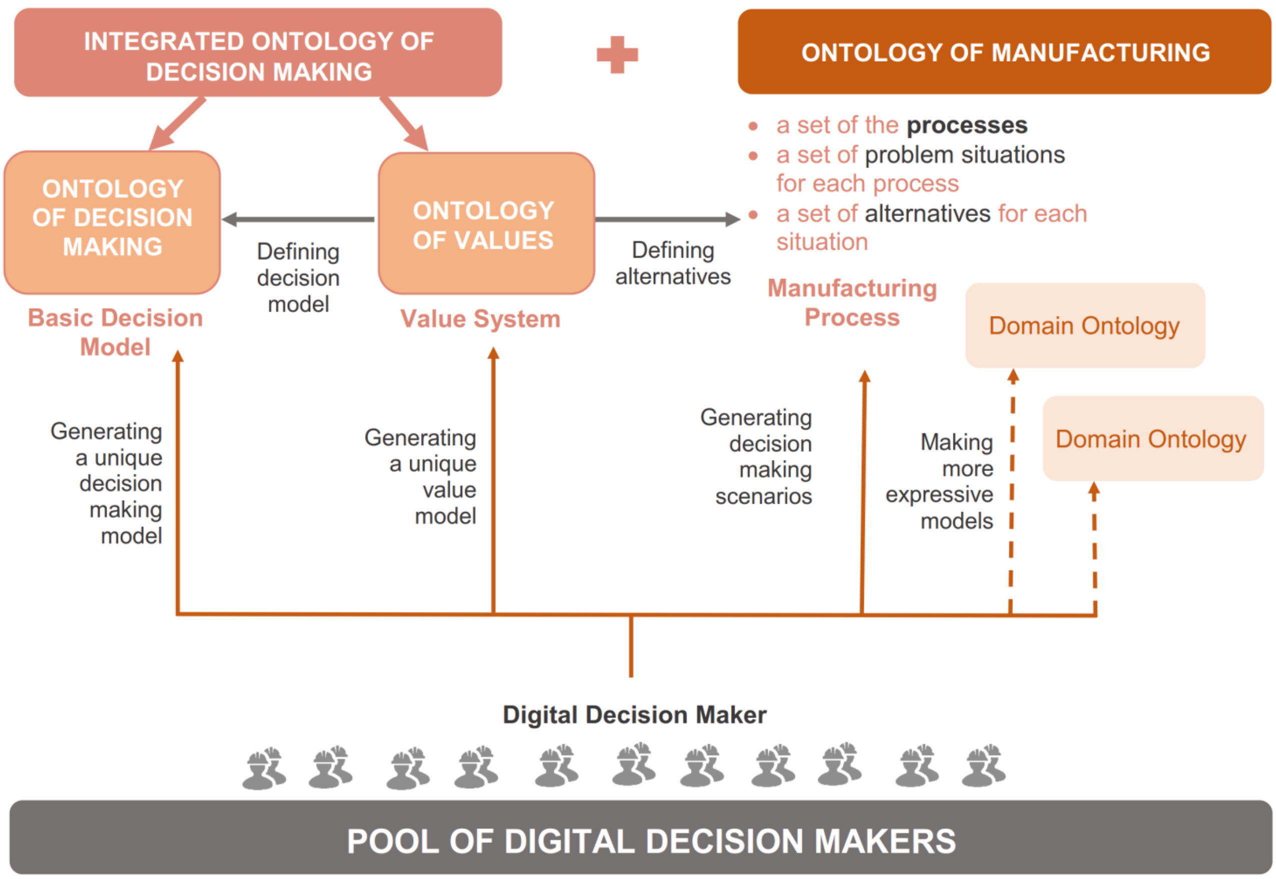

Figure 3. Model of the decision-making process

The two-layered personal decision models are kept by Pi-Mind robots, which are implemented as artificial agents according to the technology of intelligent proxies ("software robots") developed as a part of SmartResource/UBIWARE/GUN vision and technology [35,36,37,38]. The technology enables coordination of processes driven by various system components (human, machine, software and abstraction) via intelligent proxies. This allows using Pi-Mind robots as digital twins of all types of smart decision-making components in cyber-physical systems. Intelligence-as-a-Service (IaaS) in this case is a provider of human expertise which allows creating powerful intelligent applications fast, without building the tools, infrastructure or in-house expertise.

3.2 Creative Decision-Making in New Situations

CPSs integrate highly distributed and connected digital technologies that are embedded in a multitude of heterogeneous multi-scale autonomous physical systems with various dynamics. Robots are installed into dynamic, partially unknown environments. All these increase unpredictability of their behavior especially in unexpected emergency situations. Existing knowledge-based decision-making algorithms, machine learning and predictive analysis fail to address this challenge. People remain "irreplaceable" due to their unique cognitive abilities. Therefore the Industry 4.0 needs artificial decision-makers with human-like cognitive skills. Multi-criteria decision-making models are promising for designing digital decision-makers that should take into consideration diverse quantitative and qualitative factors to evaluate different alternatives.

The Pi-Mind model allows a software agent to inherit someone's decision behavior without the necessity of going through all the stages of its formation from the scratch. The methodology of decision-making is based on the parametric approach. We define a personalized set of preferences for a set of possible situations in the form of parameters valued within a scale between "good" and "bad", which altogether has been combined to a unique quality map.

Subjectivity in the decision-making is not limited to a value system only. Each person has her own idea of the freedom of actions in different situations. It is formed under the influence of factors of completely different origins:

- A cultural environment that sets out the general principles of moral behavior (including the culture of production and business interaction);
- Duties and responsibilities (both formal, which prescribed in job descriptions, and informal, which are formed as a result of established practices);
- Human development, which is understood as a process of enlarging people's choices.

Integration of the factors builds up a unique set of possible actions (alternatives) in different situations for the given person, which is a unique freedom map. Therefore, the parametric approach to decision-making is complemented by the functional approach. A Pi-Mind agent acts not only as an internal judge with the quality map, but also reflects the sense of freedom of the person with his/her freedom map.

In the regular mode of industrial operation, a Pi-Mind agent works with predefined alternatives in a given space of situations using the embedded value systems. The precondition of this mode is that the person's preferences are always tied to specific situations. The situation described in terms of the ontology of manufacturing is matched against the personal quality map and the freedom map.

However, in real-world dynamic manufacturing, it is impossible to describe all available alternatives and parameters. Still, in a new situation with unpredicted parameters, a Pi-Mind agent is required to react in a manner similar to its owner's one. The agent should observe the new realities and must be capable to generate new alternatives and parameters. In this case, a Pi-Mind agent will act as a smart cognitive system capable of creativity, cognition and computing (see Fig.4).

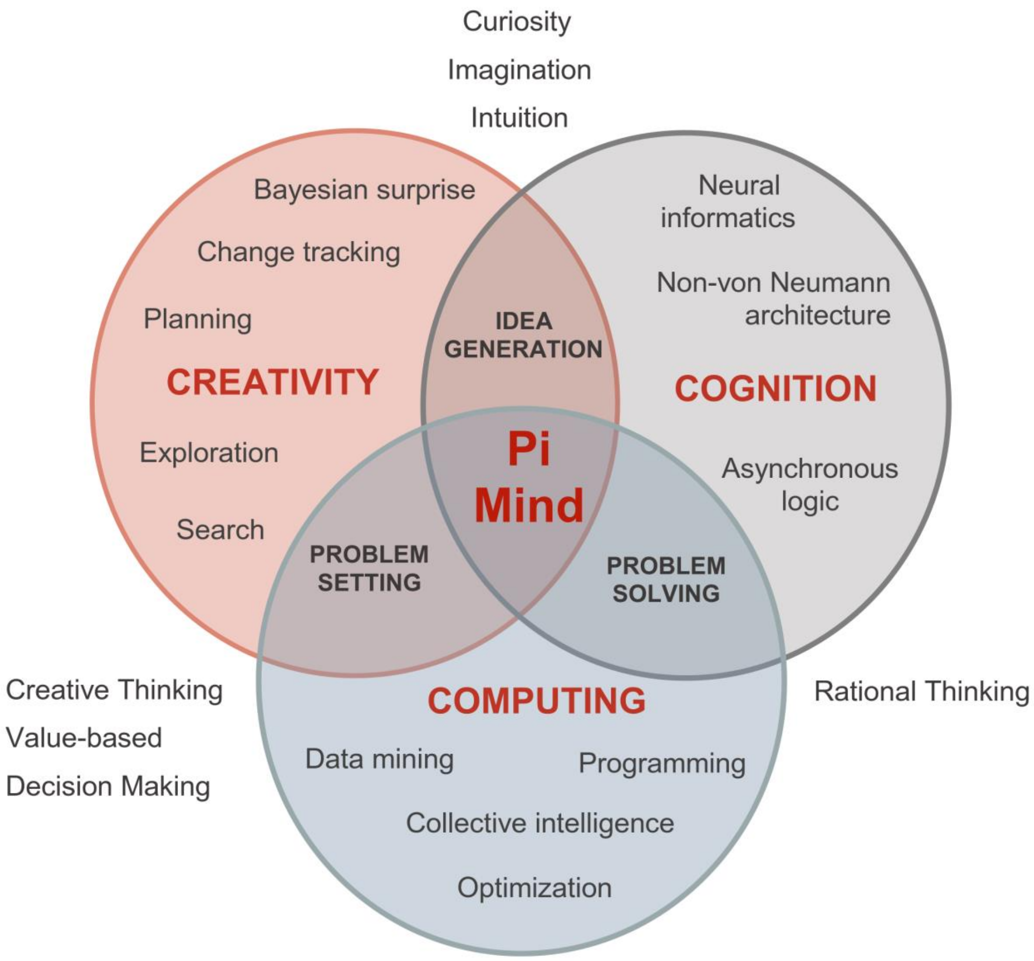

Figure 4. Relationship between cognition, creativity and computational abilities in modern cognitive systems

While traditional computers must be programmed by humans to perform specific tasks, cognitive systems learn from their interactions with data and humans on how to perform new tasks. New cognitive architectures for computing take inspiration from the human brain and use deep learning techniques to obtain insights from huge quantities of data, in order to handle complex situations, make more accurate predictions about the future and better anticipate the unintended consequences of actions. Deep learning corresponds to a specific subset of machine learning techniques and it is commonly based on deep non-linear neural architectures, which are able to process big data in their raw form enabling better human-machine collaboration. Machines are trained to perform mind-like complex computations and fulfill tasks, which traditionally required human cognitive skills such as learning, adapting, interacting and understanding. The biggest challenge for deep learning is to ensure real depth of cognition. Deep learning becomes really deep when the cognitive systems are able to approach human-like behavior not only in problem-solving but also in creativity (a new idea generation, a problem discovery and formulation, etc.). To achieve this, cognitive systems must be conscious to have and understand their own desires, intelligently form novel ideas, theories, inventions, do research, set up own goals, reach them and understand why and how.

We suggest considering a hierarchical self-reconfigurable meta-structure (see Fig.5) as a model for combining creativity and intelligence, which is based on a cascade of diverse models (such as deep neural networks). It has two dimensions of the depths: it consists of (i) a meta-level organized as a deep architecture of a cascade type, and (ii) basic level of typical deep learners, such as deep networks. In the situation when each learner of the basic level is a deep neural network, we obtain a cascade of multiple cascades.

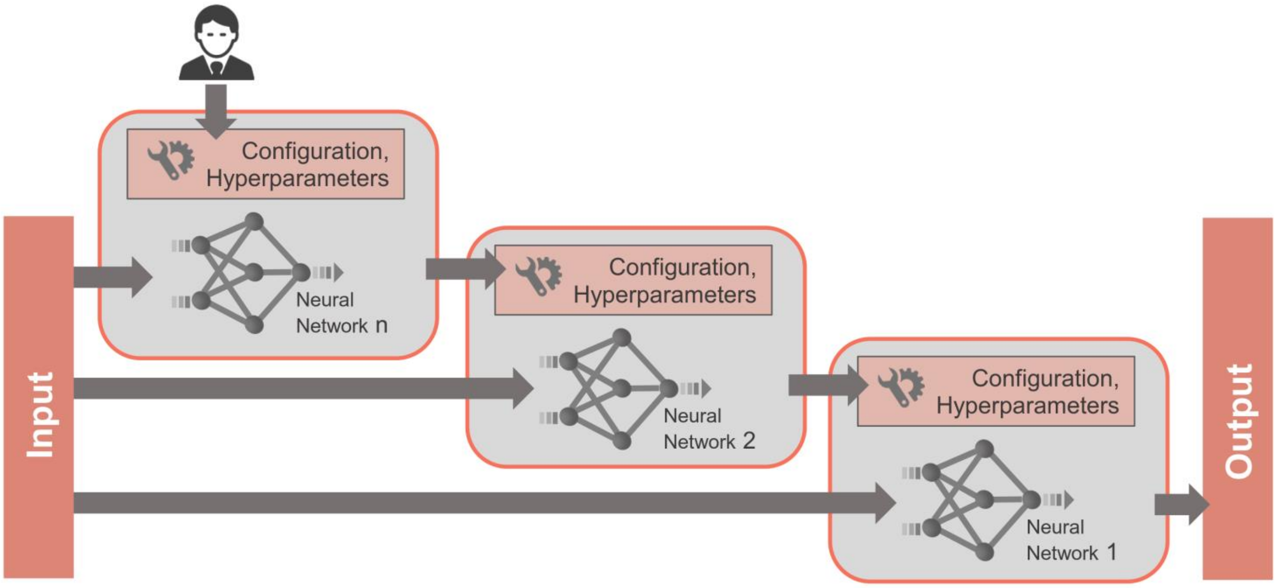

Figure 5. A hierarchical self-reconfigurable meta-structure for deep learning

The meta-model learns at each of the two levels. At the meta-level, it learns setting up and formalizing a problem in form of a cascade of specific tasks by configuring learning models of the basic level. It allows combining several specific learners into one comprehensive multi-task learning system.

The lowest layer of the meta-cascade is a model, which acts like a problem solver, i.e., takes domain inputs as a set of configured parameters of the environment and generates the target outputs. The next more abstract layer acts as a supervisor for the lower level problem solver, i.e., it computes all the configurational settings and hyperparameters needed to configure the problem solver, as well as finds, which of the domain features must be taken as the inputs. This means that the models of the more abstract layer play the role of experts who know what is the problem to be solved by the lower layer models, why they are solved and how (by which configuration). In complex cases, the layer-controller needs some automatic control and supervision coming from the next layer and so on along the cascade. The challenging task is to train all the layers to infer the configurational parameters for further supervision based on available domain features, i.e., each layer may use a different subset of the domain features as inputs. The highest layer is a model supervised by a human (owner of the Pi-Mind agent) but it works largely as a policy-maker for the whole cascade.

Meta-level cascades require some new, non-traditional deep learning approaches, while each layer can be trained autonomously as a typical deep network by backpropagation.

3.3 Value-Based Decision-Making in Virtual Collaborative Environments

The technology of cloning human decision models has been first deployed for the virtualization of the academic environment and digital twinning of the best practices in the field of higher education (HE). With these aims, the Portal for Quality Assurance of HE has been developed. It is a virtual platform implemented as a semantic portal according to the new semantic technology of ontology-based Web platforms, which are used for transparent collaboration of multiple human and artificial players [39].

The portal helps to establish a higher quality of communication between various HE stakeholders and increase transparency and quality of collaborative decision-making by transferring critical processes to the virtual environment and empowering decision makers with digital assistance. The knowledge base of the portal stores hundreds of digital clones of academic experts who shared their value systems making them not only transparent but also executable and reusable.

The core function of the portal is the quality evaluation. It is a highly biased procedure due to the controversy of the quality concept and numerous possible interpretations of it. However, quality evaluation is an important component of decisions made at various levels of the education system, beginning with a choice of an employee for a position, and ending up with the definition of national or global education strategy goals. Quality formalization and assessment is strongly dependent on the value systems of responsible decision makers, groups of policy-makers and national authorities. Digitalization allows making "the rules of the game" transparent and gives to the users a tool for further "consultations" with trusted digital experts in order to see the situations through their "eyes" by applying their value systems for alternatives' assessment.

Each user of the portal can evaluate the HE resources from different points of view, representing various stakeholders and world-ranking systems. The portal ranks alternatives according to their relative quality defined by decision maker preferences, which are linked with the Ontology of Values (see Fig.6).

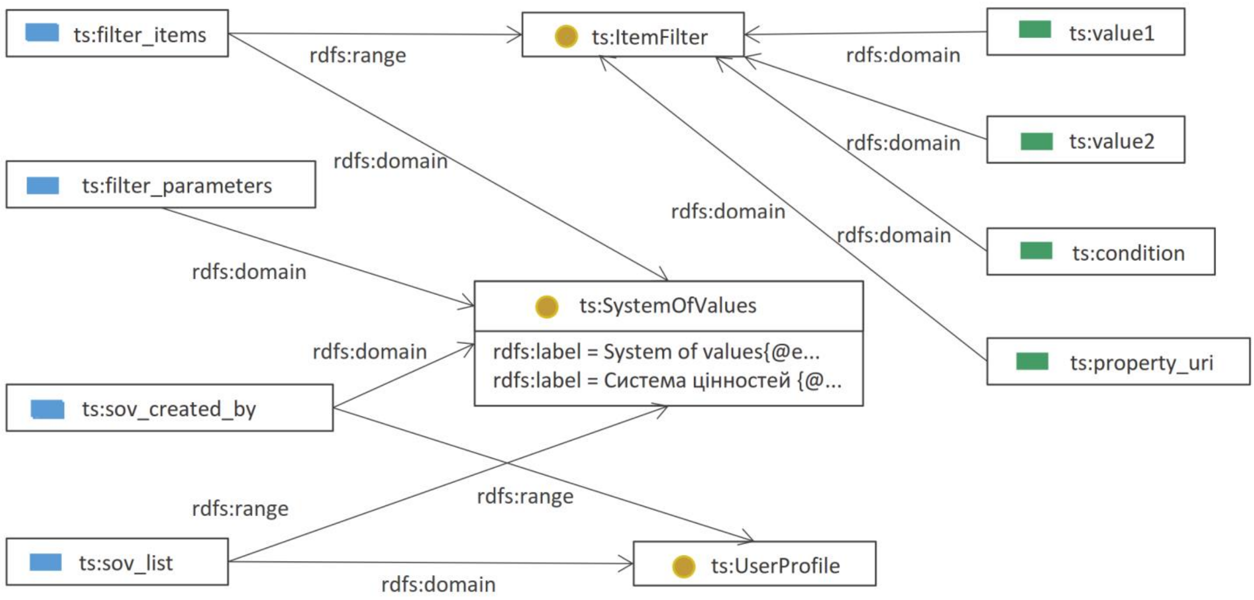

Figure 6. The ontological model of a personal system of values

A preference vector of numbers from the [0,1] interval shows the relative importance of the quality criteria (see Fig. 7).

The preference vector supports the multi-criteria decision-making based on the weighted sum model [41]: each entity (e.g., a University) obtains a numeric value (cost) as a result of evaluation of all its achievements (e.g., papers published by the university staff) calculated by:

$$EntityCost = \sum_i (userweight_i * value_i), \tag{1}$$

where $value_i$ corresponds to a value of all achievements of the same type and $userweight_i$ is a user-defined weight for the type in the chosen ranking system for the current evaluation request.

The value for all achievements is calculated as:

$$value_i = \sum_j (resourceweight_{type} * impact_j), \tag{2}$$

where i is an achievement instance in question, $resourceweight_{type}$ is a default value for the type of the achievement being inversely proportional to the number of the achievements of this type (rarer achievements are more valuable) and $impact_j$ is an impact of the achievement calculated differently for achievements of various types (e.g., scientific papers have citation-based metrics for impact calculation).

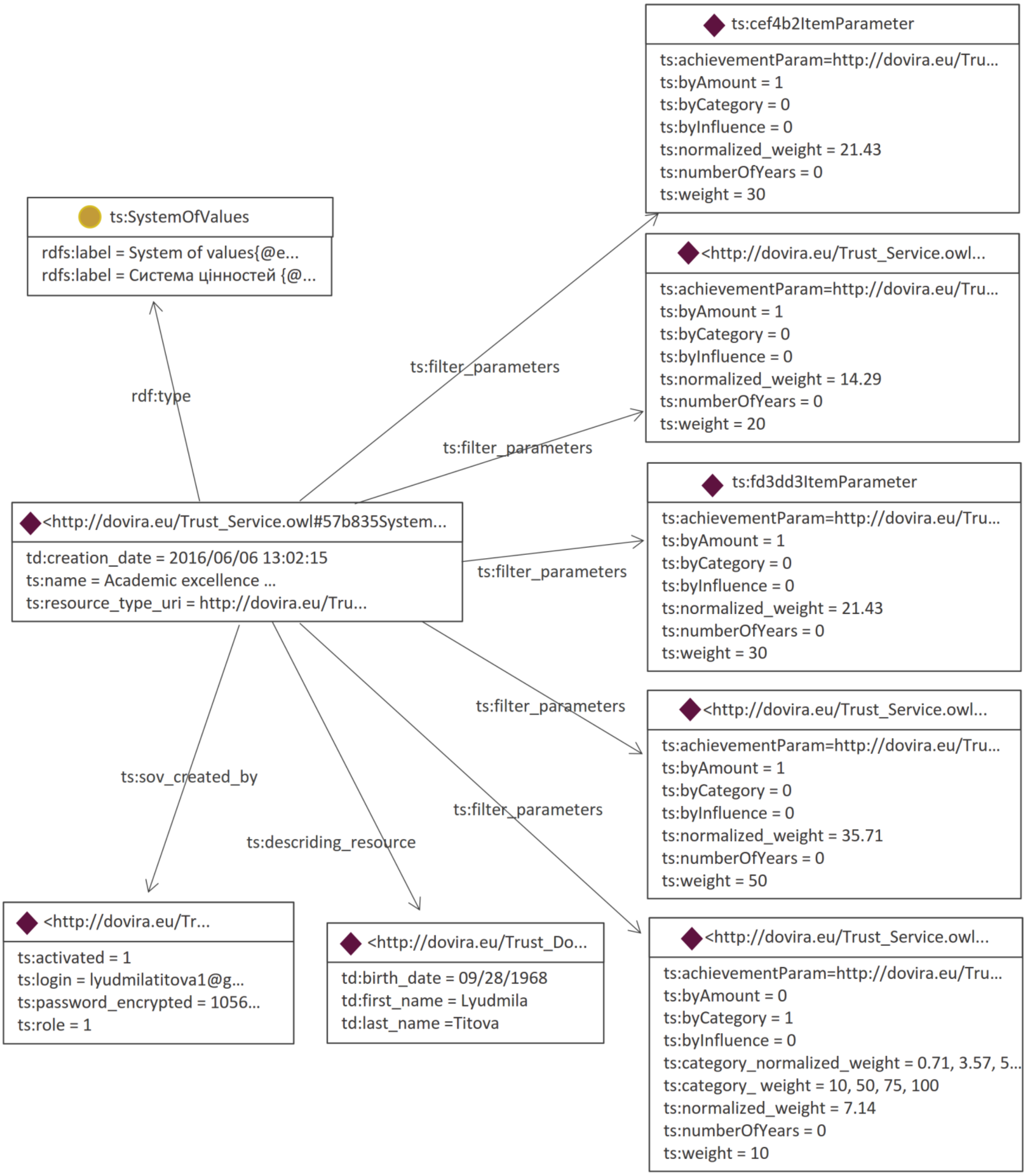

Figure 7. The example of a decision taken by a digital expert

3.4 The Place of Pi-Mind in Industry 4.0

The proposed Pi-Mind concept corresponds to the spirit of the Industry 4.0 and allows transferring from a common vision and philosophy of industrialization to a specific technology and its industrial implementation. The industrial use of Pi-Mind requires the determination of the place and the role of this new technology in the industry value chain. The overall business value is defined as the total benefit brought to the customers and the ability to satisfy their needs. It is measured by the revenue, which reflects the "monetary vote" of customers in favor of a particular product/service.

Therefore, the appropriateness of any production innovation is considered according to the key concepts of the business model:

- value – what the consumer needs, for which he is willing to pay money;
- value driver – what ensures the appearance and growth of the value;
- enabler – the tools that physically implement the functionality of the drivers.

The concept of Pi-Mind in terms of value chains is presented in Table 3.

Table 3. Value chain for industrial use of Pi-Mind

Business model elements	Industrial application of Pi-Mind
value	1. Higher productivity of industrial manufacturing (optimization of cost-effectiveness ratio) due to faster and more accurate choice at critical points of decision-making. 2. Pi-Mind-enabled functionality of the end product.
value driver	Pi-Mind-services as decision-making support in the production process: - Storage, share and reuse of personal value systems in production systems. - Patenting and selling various types of Pi-Mind licenses (single, package, urgent) for external use. - Expert councils based on Pi-Mind-expertise. - Science-shops.
enabler	Collective intelligence as a combination of human intelligence, Artificial Intelligence and Cognitive Intelligence

The Pi-Mind's solutions correspond to the main requirements of Industry 4.0 (see Fig.8). The concept, although based on the development in the field of Artificial Intelligence, does not offer its introduction into production in its classical form. Here it is an issue of creating a unique collaborative decision space, where physical objects are digitized and seamlessly integrated into the information network.

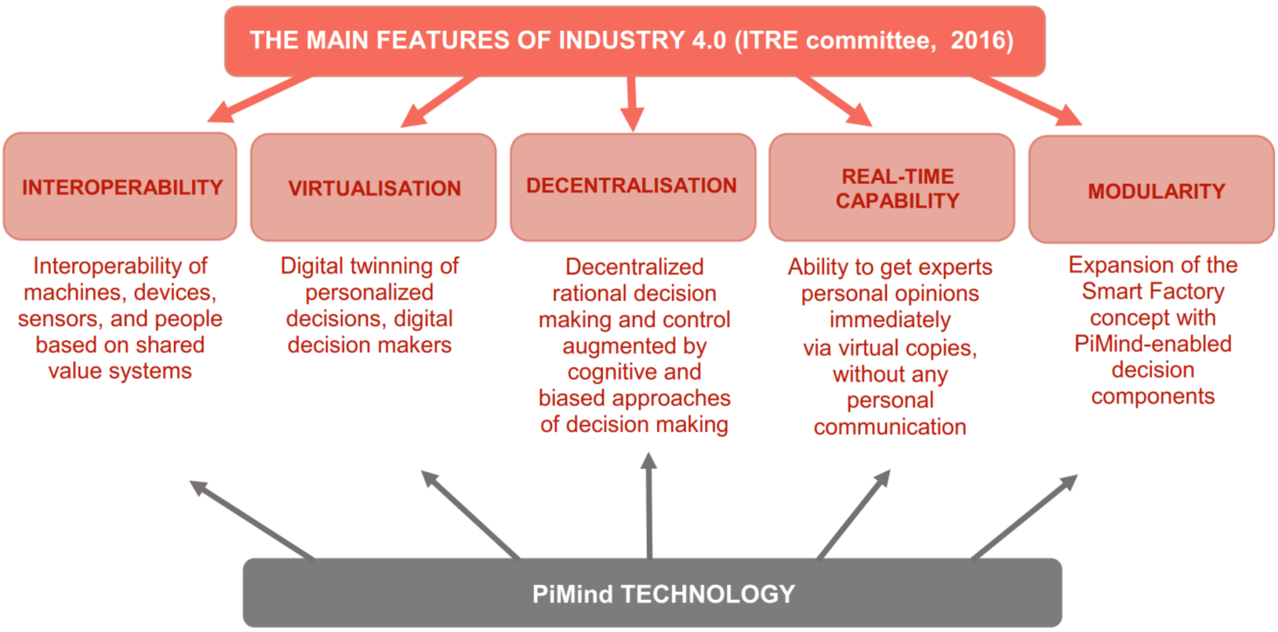

Figure 8. Pi-Mind as a part of Industry 4.0

The place of the Pi-Mind in Industry 4.0 can be determined according to the scheme of the development of analytics in the industrial context [41] (see Fig. 9). The new industrial paradigm is changing the roles of human and machines in the production processes. It is restructuring the very essence of the concept of "workforce". The increasing complexity, knowledge intensity and intellectualization of industrial products are the reasons why the main share of human jobs will be taken by highly skilled professionals with more and more specific specializations. Today, the problem of experts' involvement is solved by outsourcing or temporary employment because of the high cost of their work and the need to use their skills and abilities fragmentary. This creates the following risks:

- the likelihood of production interruptions increases due to the inability to ensure instant engagement the required employee in the needed place;
- the possibility of industrial secrets leaks increases;
- the flexibility of the production process is reduced due to the weak control of the personnel.

These risks create a serious threat to a business – the workforce challenge. They undermine the main principles of Industry 4.0: real-time, mobility, multi-skilled teams and agility.

Pi-Mind is a compromise on top of Collective Intelligence emergent from the collaboration of artificial and human individuals. It implies that highly skilled professionals can participate in key aspects of business processes (where none of them will be replaced by another employee or artificial entity) spending none of his/her time for physical or online presence, but having a possibility to contribute by his/her personalized (subjective) expert opinion.

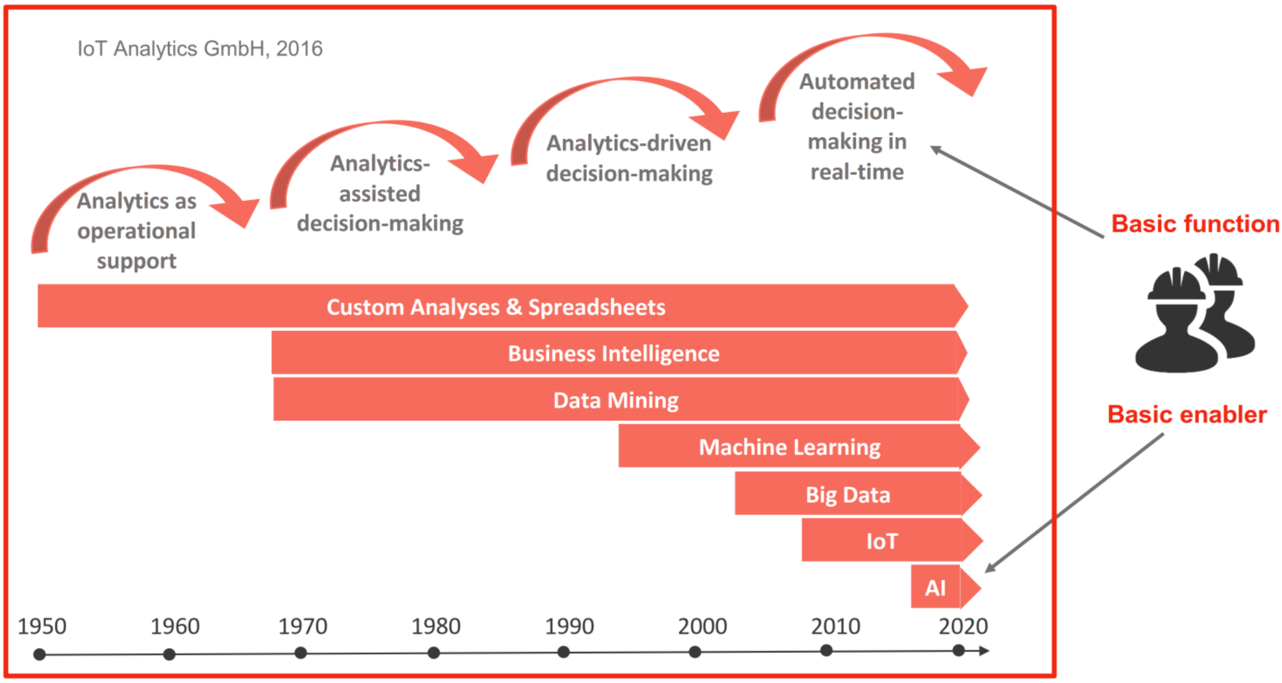

Figure 9. The place of Pi-Mind in the context of industrial analytics evolution

The task of the Pi-Mind agent in industrial context is not on removing the human-in-the-loop from decision-making, but to improve the decision quality by seamless integration of a human with the IT technologies.

Pi-Mind technology can be used as a solution to the "workforce challenge" which enables a shift from human employees functioning approach to the service-oriented one in almost all the decision points of industrial ecosystems. A human usually has a certain degree of freedom in making decisions: from specification and monitoring to verification of the production strategies. Of course, the standards of industrial production limit the actions of the producer to the technological parameters, predefined processes or sequences of actions and the rules for their implementation. However, even framed by these restrictions, each employee acts uniquely and earns his own skills and abilities.

The freedom of an employee's choice and related personal responsibilities are the points where the Pi-Mind technology can be applied naturally. It allows an employee, in addition to his subjective assessment of any situation (particular production state or problem), rely also on the digitalized experience of his colleagues, experts or well-known or respectable specialists. These can be done instantly without involving actual people but using the Pi-Mind robots as their representatives for flexible problem-solving. Figure 10 shows how the Pi-Mind can enhance the workforce in the industry.

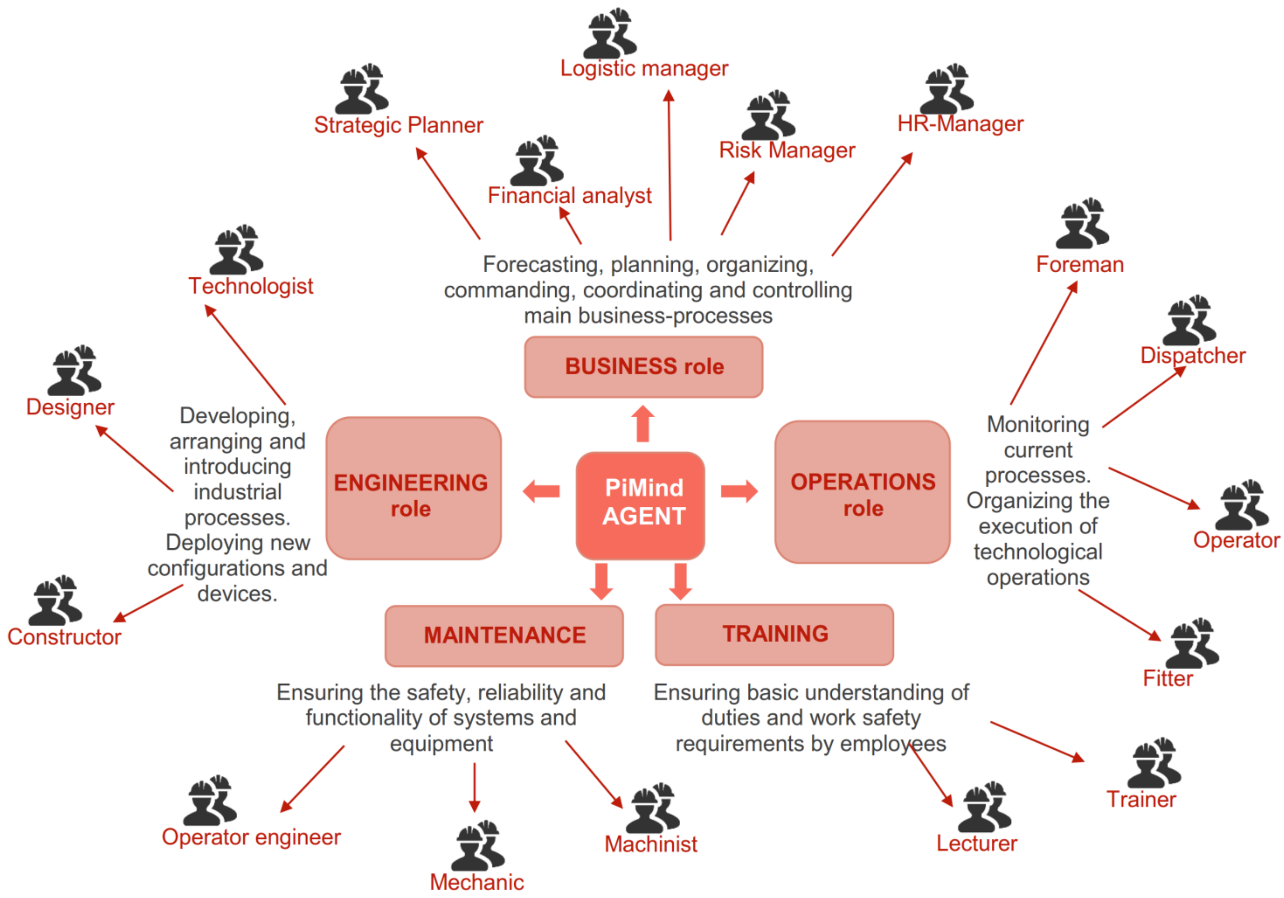

Figure 10. Industrial applications of Pi-Mind

Pi-Mind agents can be integrated into the key production services of Industry 4.0 (Table 4).

Table 4. Examples of production processes for Pi-Mind agents' engagement

Group of Services	Use of Pi-Mind agents
Process monitoring services	Observation of the process by not only human operator, but also by experienced Pi-Mind robots for rapid detection of deviations
Dispatching production orders	Adaptation of the flow of batches' runs and work orders to unanticipated condition (in particular, in manufacturing execution systems)
System diagnostic and maintenance service	Control the health and condition of shop-floor equipment, machinery, devices, SCADA systems and PLC, etc., and make predictive/preventive maintenance decisions
Alarms service	Alarm handling, when an operator has to acknowledge the alarm event and make a decision about further actions
Knowledge management	Keeping and transferring work experience
New products design	Creation of highly skilled engineering expert groups including Pi-Mind agents for flexible product development. Creation of a client's Pi-Mind robot for customization of products and specification of customer requirements in real time
Security service	Creation of a team of Pi-Mind agents specializing in various aspects of industrial security (from physical and technological to a virtual one)

The decrease of direct engagement of human labor force in production is the main economic impact of the Pi-Mind agents' introduction. It has two important components: increase of production efficiency and employment reduction. The latter is often perceived as a total increase in unemployment and therefore, causes fear. In fact, there is an ongoing change in the structure of employment. The Pi-Mind allows reducing the time for a monotonous work, releasing time for creativity. Indeed, this will cause changes in the labor market: both the requirements for the profession and the list of the professions. According to one of the estimations of the World Economic Forum [42,43], "65% of children entering school will ultimately work in jobs that don't exist today, putting creativity, initiative and adaptability at a premium".

Though the introduction of the Pi-Mind will reduce the demand for domain experts, but it will facilitate the impact of the best of them (due to ubiquitous presence) in smart manufacturing processes. Anyway, there will appear an additional demand for various kinds of experts around Artificial Intelligence and related technologies. Such changes are not easy, but unavoidable. Therefore, the idea of the Pi-Mind is not about replacing human in industrial processes; it is about making every particular human ubiquitous, i.e. capable of making a more global personal impact within Industry 4.0.

Not only labor force is in the focus of economic impact of the Pi-Mind technology, but also changes in the entire structure of productive resources. Pi-Mind accumulates the unique professional intellectual capital in form of value systems of employees, experts and decision-makers. The economic value of Pi-Mind technology is created by the following mechanisms:

- identification of the intellectual capital and transferring the intangible value of the business (knowledge and experience of employees) into its assets;
- capitalization of the knowledge and experience of employees - Pi-Mind agents can stay in the company even after the actual workers leave (if this is stipulated by the contract);
- monetization of intellectual capital through the patenting of Pi-Mind agents, which gives legal grounds for their distribution.

4. Application of the Technology

4.1 Industrial approbation of the Pi-Mind technology

In Industry 4.0, a typical supply chain is fully integrated: it seamlessly connects manufacturing, maintaining, distribution and customer relationship management processes and includes the following elements:

- complex orders: the supply of industrial equipment is not the same as the end-product purchase, it is a separate project, which is expected to meet specific requirements from a client.

- Installing equipment in the manufacturing process: the delivery does not end with the distribution. The uniqueness and high level of industrial solutions require a sensitive adjustment, proper installation and fulfillment of warranty requirements.
- Expert maintenance for complex industrial systems.

In such supply chain, the decision space cannot be clearly divided between the distributors and the industrial customers. The adoption of a particular supply-chain solution requires mandatory participation of the customers, and, vice-versa, the needed installations require participation of equipment experts. This participation does not take place on an ongoing basis but is realized in the form of request-response. Since some of the requests are fuzzy and cannot be automated, they must be processed individually by relevant specialist. It distracts workers from their basic work and creates delays in time. This challenge can be addressed by the Pi-Mind technology.

One of the first industrial cases of the Pi-Mind technology was related with the company Focus VD, which assembles and distributes compressor equipment in Ukraine. The company works with advanced compressed air technologies. It appeared to be a relevant place for the industrial implementation of the research results due to several reasons:

- the value chain of the company comprises a set of various industrial logistics processes: from the distribution of compressors from all over the world to the assembly of compressed air systems. The company's clients' list contains enterprises with absolutely different technological processes, such as, a large plant Turboatom, which is among the top ten turbine construction companies in the world, or a regional dental clinic.
- The company develops and actively introduces both automated logistic systems and multi-criteria decision support systems. They ensure smooth flow of the activities in the value chain and increase its efficiency in terms of timing, quality and quantity.

The Pi-Mind technology has been installed into the supply chain of the company and tested in the real environment of the company (Figure 11). In the experiment participated 3 employees of the company with different specializations related to assembly and installation of equipment at customer sites, and one anchor client (a plastic containers factory, where compressors are the key elements of the production systems).

For the creation of a "virtual proving ground" of the Pi-Mind technology, we developed an ontological platform and trained four experts on how to create and configure their Pi-Mind agents (further carriers of their unique value systems). During a month, Pi-Mind agents worked in the background mode:

- requests were sent to both the anchor client and its software agent for new orders creation;
- requests related to compressors' assembly were sent to the experts who worked at customer sites and their agents;

- during compressed air systems' assembly on the factory floor, requests were sent to the experts who worked in production and their agents.

237 queries were processed during the testing period. The decisions of agents and their owners coincided in 216 cases (91%).

9 agents have worked in Focus VD since August 2017. This impacted on the decrease of the number of the pending requests for decision-making when decision makers were away (60% on the average during a year).

The experiments revealed three types of immediate effects:

- decision-making is performed without quality decrease (with expert support);
- time-saving for employees and clients;

reduction of the work tension because of the frequent small inquiries to experts, which detracted them from their ongoing work.

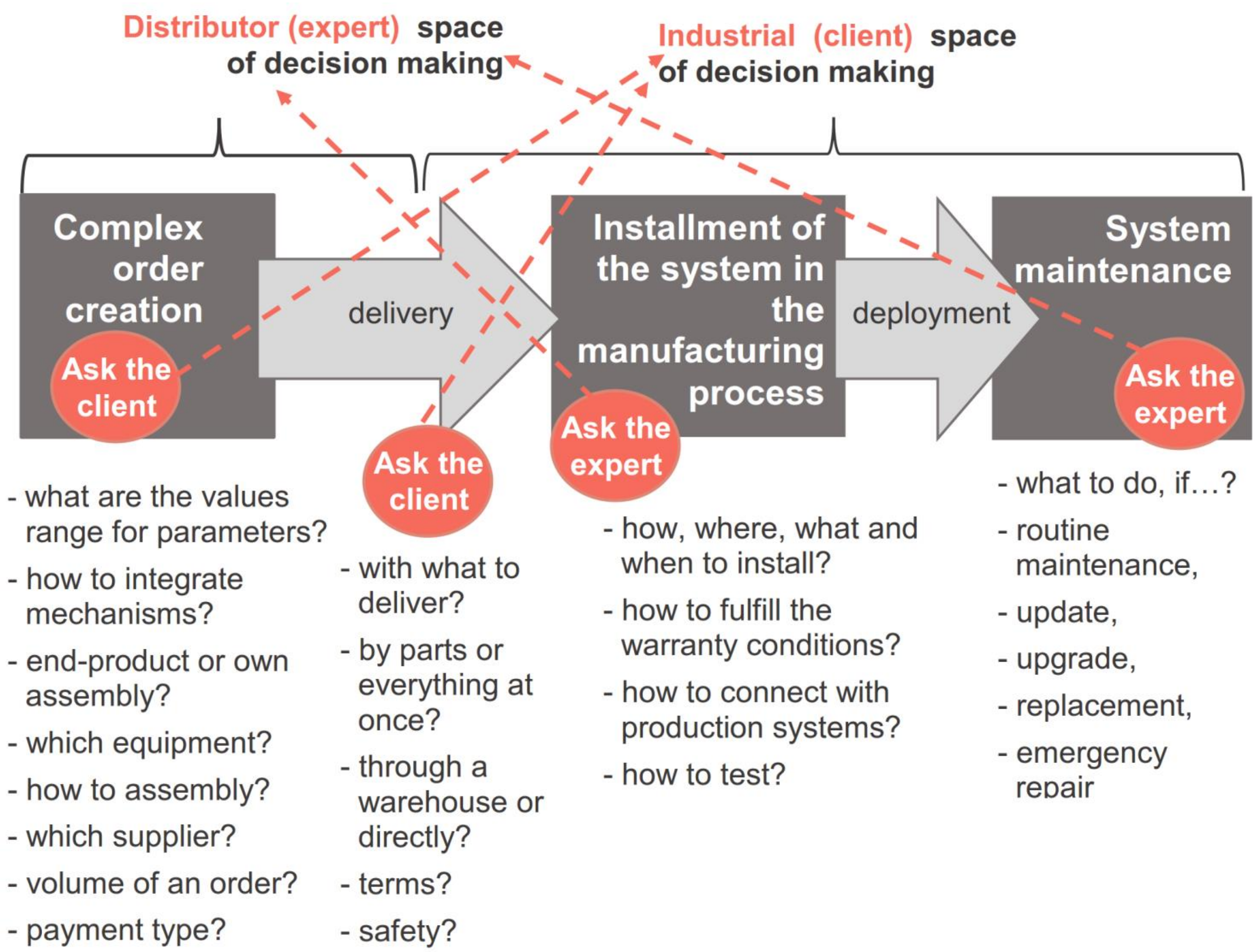

Figure 11. The map of solutions for Focus VD

4.2 Several possible use cases for Pi-Mind technology

Use case 1: Collaborative mass customization of short lifecycle products. Mass customization means an increase of the variety of possible versions of the same product or service, and, therefore, the possibility to make a good choice is important for the customers. Collaborative mass customization helps to find the needed product for a user (who is confused by a huge variety of options). The Pi-Mind technology gives a ground for products customization. By tuning once a Pi-Mind robot (the holder of the customer's decision-making system) and connecting it to the manufacturer, the customer in fact creates own virtual representative who will be acting on behalf of him/her during all the stages of the production, delivery and installation. Robots may join the groups with similar preferences and may be used for acquiring structured feedback regarding new products. Pi-Mind robots may become a core technology within, e.g., the smart car factories as these robots help to make decisions and contribute to the customization of products.

Use case 2: Worker assistance in assembly and testing. Pi-Mind robot assists a worker who makes creative decisions in the situations where some improvisation is allowed or even encouraged. In addition to his personal Pi-Mind robot, the suggestions from the artificial clones of several other experts can be taken into consideration to infer the integrated, compromised and possibly unique decision for a particular problem. The worker benefits from the diversity of opinions and can make the grounded decision. The Pi-Mind robot tuned by the worker can also substitute the owner in manufacturing processes, which are not rigid and adaptive.

Use case 3: Virtual quality controllers and managers, e.g., lean managers who ensure the quality of manufacturing processes and intended products' assembly. Modern companies have lean but rigid production lines, which imply isolated solutions, together with few separated quality control points resulting in costly process shifts and wastes in production. The profitability, efficiency and quality of manufacturing can be assured by adaptive lean management system introduction, permanent quality control and in-time solutions by experienced (certified) experts-practitioners with specific skills and knowledge on lean implementation. The Pi-Mind technology supplies a human lean expert with a tool for creation and tuning of their own robots (artificial lean experts with the owner's unique decision system). A collection of robots, primarily supplied by the professional experts (certified Lean Black Belts, Lean Green Belts, Lean Six Sigma Black Belts) and accompanying services can be stored on the e-market of lean robots. A company can purchase a robot or a collection of robots to deploy a lean production system. The robots are sold by a special license. The owner of the robot gets a fee for each purchase of the robot on the market. Deployment of the network of digital lean experts helps meeting challenges and pressures of manufacturing processes demanding a full-time presence and involvement of lean experts, achieving perfect workflow, minimizing waste and assuring production flexibility.

Use case 4: Autonomous driver. There has been a significant research effort dedicated to the development of the intelligent driver assistance systems up to an autonomous driver. The main focus of the systems is on the methods of monitoring and predicting the development of a traffic situation and choosing an appropriate car action with respect to the driving objectives, the environment state (utility function is used for calculation of the value for each possible environmental state) and driving rules. This means that a self-driving car chooses an alternative based on its internal decision system knowing nothing of the owner's preferences and driving style. The decision is typical for the car driving system and will stay the same for all other owners of a similar autonomously driven car.

According to the traffic psychology, the safety of a trip depends on various factors, among which the driver's comfort zone caused by the following variables: safety margins; good or expected progress of the trip; rule following; vehicle/road system; and the pleasure of driving. An unfamiliar car self-driving system's style, unsafe feelings or unpleasant trip can become a serious factor in car accidents or denial to use the intelligent driver assistant. Enhancement of the car self-driving system can be done by programming the system based on the owner's driving style, which utilizes the owner's decision system on the road. The driving system will work on top of three models: the basic one defined by the standard driving rules and installed during the car's manufacturing; the customized model based on the user's system of preferences tuned during the car's exploitation, context (by additional domain ontologies) influencing the driving style (children in the car, time left till the boarding on the plane is over, health factors, etc.).

Therefore, a driver creates a driving robot based on the Pi-Mind technology. The robot is mobile, autonomous and can be used for various vehicles. Customization of the car's self-driving system can enhance mutual "understanding" between an autonomous driver and a human driver decreasing the risk of car accidents; it will be able to give answers to some ethical questions related to the responsibility for the self-driving system decisions.

Appropriate business model can be built on top of a collection of patented robots primarily supplied by the professional drivers and auxiliary services, which are stored on the e-market of driver robots aggregating buyers and sellers. A buyer can purchase any driver robot to install in the car. The robots are sold by a special license. The owner of the robot (the one who uploaded it to the e-market) gets a fee for each purchase of the robot on the market. Buying a robot of famous people or even celebrities can be interesting for their fans. A robot with a calm behavior can be a choice for those who start driving. Robots of a British driver can be bought for a journey to Great Britain.

Use case 5: Automotive industry. This industry is the most rapidly developing one in terms of Industry 4.0. Table 5 shows possible applications of the Pi-Mind technology for the industry.

Table 5 – Possible applications of Pi-Mind for car manufacturers

Company	Process characteristics	Points of implementation for Pi-Mind
Volvo Car Corporation (Sweden) & Siemens PLM Software (the USA)	To address its growing engineering and production challenges, Volvo Cars is now using various tools from Siemens PLM Software [44]. The manufacturing process management capabilities of Teamcenter® and several tools of Tecnomatix® software are used to manage, plan and simulate production processes.	Employment of new process simulation tools, use of robot capabilities and smart agent technologies, such as Pi-Mind, can help addressing the growing expertise requirements of the company. The Pi-Mind technology can also enhance welding and gluing processes which are now performed by programmed robots and the Tecnomatix tools. It can make cooperation of the Volvo engineers and Siemens personnel smoother and more effective.
Ford Motor Company (the USA)	Global Director of Interaction & Ergonomics heads up the team that is pushing Ford to the cutting edge of human-machine interaction (HMI) [45]. The ultimate goal for Ford's HMI team is to understand and validate the technologies to be useful, usable and desirable.	Ford uses a set of quantitative and qualitative research activities to get to know the Ford customers – who they are, what they want from a vehicle, and how they use its features to get the job done. This research can be essentially facilitated by the capabilities of the Pi-Mind technology (see use case 1).
BMW AG (Germany)	The Analysis Center of BMW is a fully functioning laboratory that allows examining and testing every weld, every dimension, and every component on vehicles as they come off the production line. The Analysis Center covers three key areas of vehicle development: Functional Analysis, Manufacturing Analysis and Customer Feedback [46].	The Pi-Mind agents can be used for: - functional analysis and simulations to test how the car feels; - manufacturing analysis to find the best way to bring resources to bear in the production; - digitalization and formalization of customers` feedback.
McLaren Group (the United Kingdom)	The assembly process by McLaren, tooling, and stillage are bespoke. Every component is presented as jewelry, and every production technician is an expert in their field. They create cars around an owner's precise tastes. The mission is to make what is already special into something truly unique [47].	- The assembly process, tooling, and stillage can be enhanced and expanded by digital experts and technicians. - Pi-Mind agents can represent McLaren customers and their unique requirements and wishes.

5. Future Research Directions. Five "I"s

The Pi-Mind technology provides flexible models, techniques and tools which can be further developed within various dimensions to support the needs of Industry 4.0. There are five most obvious vectors for the further development of this technology, so-called five "I"s: integration, intellectualization, interaction, infrastructure, and implementation.

Deeper integration of the Pi-Mind technology into production: "Smart consultants" can already now be offered as an MVP (Minimal Viable Product) when implementing the Pi-Mind technology within the industry. Their main task is to give production recommendations, e.g., for maintenance of the equipment, for reconfiguring the production process or for adjusting the schedule of the operation. At the initial stage of implementation, such "smart consultants" may not be able to fully reproduce the human decision-making process. A factory is a complex physical system where failures are possible. The data about the state of the factory environment is collected by a huge amount of sensors and communication channels, which can produce errors and distortions. In addition, potential and real failures may be very different, have different properties and parameters. To make decisions, a decision maker needs confidence in the completeness and accuracy of the data. While this problem is not solved, the "smart consultant" will not completely replace a human decision maker. The more sensitive and reliable sensors will be available the higher the efficiency of the interaction between virtual and physical processes in production would be possible. A "smart consultant" can also improve itself by acquiring new experience and knowledge. Pi-Mind technology can be fully integrated into smart self-organizing systems when Pi-Mind agents will be able to perform the tasks of decision-makers in autonomous production.

Intellectualization of the Pi-Mind agents: Self-awareness of a person, his/her self-esteem and self-management allow identifying a unique set of the preferences and possible actions in different situations, and also a set of possible dimensions for development. One of the promising directions of the technology intellectualization is the further development of the deep learning techniques for Pi-Mind agents based on quality and freedom maps, cognitive computing and computational creativity.

Interaction of Pi-Mind agents: the work of the Pi-Mind service can be organized through the use of: just one Pi-Mind agent as a separate expert (from a consultant to a decision-maker); groups of independent Pi-Mind agents to obtain a range of expert opinions on some issues; multi-agent system, where the Pi-Mind robots interact with each other and the external environment to solve problems. Self-organization of the Pi-Mind agents in such systems is provided by swarm intelligence.

Infrastructural solutions for the technology: Pi-Mind agents in the industry require appropriate service infrastructure. B2B requires IT platforms for specific enterprises for preserving decision models and using Pi-Mind agents for the production processes. Companies need also a support service with a unique set of IT functionality. B2C requires an open web-based Pi-Mind agency with functionality to support the market offer of Pi-Mind-agents. The resource must be usable, with a friendly interface to provide means for creating, patenting and selling the Pi-Mind agents. It is necessary to develop a business model that would cover various schemes for using Pi-Mind agents (one-time license, subscription, etc.) to generate a cash-flow. The resource should contain both a transparent ranking system for Pi-Mind agents, a reputation system, a verification system, feedback from the users, etc. This is the basis for ensuring the quality of future Pi-Mind-based products. The creation of the infrastructure of the Pi-Mind services includes a number of technological, organizational and commercial challenges, the answers to which are in the sphere of concrete real productions and practical implementations.

Implementation of legal aspects: autonomous Pi-Mind systems must be designed so that their goals and behaviors are consistent and complementary to the human values in all aspects of their work. The legal and ethical status of the Pi-Mind agent is still very vague. There are 4 groups of stakeholders of the Pi-Mind services: owners of Pi-Mind agents (people whose value systems are preserved), users of Pi-Mind agents (those who acquire a license to use the Pi-Mind agent), creators of Pi-Mind agents (a team of specialists engaged in the process of preserving and supporting Pi-Mind robots), developers of the Pi-Mind technology. To divide the responsibility zone among them is not only a legal but also a moral challenge, typical for the introduction of many advanced systems of Artificial Intelligence in Industry 4.0.

6. Conclusions

In the current settings of the industry, which evolves towards a higher level of autonomy and self-management, the role of humans becomes uncertain. Emerging advances in AI, particularly in Deep Learning, look very promising. Artificial decision-makers and problem-solvers are believed to be soon capable of making faster and more accurate decisions than humans and replace human employees completely in smart factories. However, the best practices, success stories and concrete examples of human-like (intuitive, emotional, irrational, etc.) decision-making may still contribute to the overall intellectual capacity of future smart enterprises. We introduce an instrument to preserve, share and reuse practices and models of the best decision-makers as a kind of "canned intelligence" and embed it into appropriate decision points of various processes within Industry 4.0.

We suggest the Pi-Mind as a technology for capturing, cloning and patenting essential parameters of the decision models taken from the best-known human decision makers and making such models proactive, executable and capable of autonomic decision-making within Industry 4.0. We consider the Pi-Mind as a compromise between total human control over decisions and total AI control of it, bringing a middle layer in between – "mind clones" (agents) of humans rather than fully self-learning artificial decision makers. The technology facilitates the human role in CPS and activates the strong human-machine collaboration. It is an example of an Intelligence-as-a-Service provider for smart cyber-physical systems enabling formalizing, licensing, sharing, reuse and integration of the personal value-driven decision models via agent technology. The potential impact of the technology can be obtained in the situations, which are usually and creatively processed by humans when there is no rigid universal solution. Such situations happen when the decision should be made in a new or emergent situation, under uncertainty or in the conditions of the dynamic environments when traditional machine learning and predictive methods do not work.

We also consider scenarios where the Collective Intelligence teams (humans, robots and Pi-Mind agents) will be capable to drive processes in Industry 4.0 by finding reasonable compromises.

Benchmarking and the search for the best practice will allow enhancing human-like (intuitive, emotional, irrational, etc.) decision-making. It will contribute to the overall intellectual capacity of future smart enterprises.

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