Digital Twins and AI in Smart Motion Control Applications

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***Abstract*—Recently, smart system integration was identified as a key competence for optimizing machines and robots. However, when one wants to 'tune' the entire production process a step further is necessary. We should evaluate performance indicators (*e.g.* energy and material consumption) over the whole machine life cycle in order to align the production with circular economy principles. To reach that target MBSE (model-based system engineering) should be covered by advanced digital twin approaches which allow continuous monitoring of machine performance, predict the failures and maintenance. Moreover, artificial intelligence and machine learning must be used to process big data sets gathered from the production lines. This paper identifies a common set of technologies and building blocks suitable to solve above mentioned problems for a large variety of industrial domains (semiconductor production, health-care robotics, CNC[1] machining, high-speed packaging and others). It presents the first results of the large-scale IMOCO4.E[2] project and shows the pathways for application of the technology on specific machines (so-called pilots). The authors believe the ideas presented could be inspiring also in other domains.**

***Index Terms*—smart system integration, mechatronics, motion control, digital twin, electronics systems, wireless communication, smart sensors, robotics, embedded systems, machine learning, artificial intelligence, cyber-physical systems**

I. Introduction

In recent decades, engineering sector must deal with limited material, energy and human resources. This implies completely new requirements also for the industrial production and related machines. Consequently, digital twins and AI[3] are being employed also in mechatronics and smart motion control applications [1]. Clearly, such applications need to follow the latest advancements is sensing ([2]–[4]), actuation, control system design ([5], [6], [11]) or novel computing platforms ([13], [14]). Hence such complex approach is relevant for many engineering domains such as semiconductor industry, health care systems, CNC production, packaging, etc [15].

More specifically, the main challenges identified are:

- in order to save material, energy and shop floor space, the machines/robots size and weight are decreasing while safe interaction with humans is needed, hence their mechanical structures are becoming more flexible [16] and problem of residual vibration appears ([12], [17]),
- raising customer demands are forcing machines/robots speeds to be close to the physical barriers,
- the machines/robots are composed of more complex kinematic architectures, often redundant and collaborative with numerous axes to be simultaneously controlled [7], [22],
- ensuring energy efficiency of machine and robot operation is highly challenging as the machines/robots must quickly self-adapt to new tasks and repeat them ([18], [21]) quickly and precisely in non-deterministic environments, producing smaller sets of customized products,
- increasing demands on product quality do force machines/robots to work in complex multi-stage production lines with integrated zero-defects and predictive maintenance at the system level,
- inclusive and resilient manufacturing is a future challenge fostering a lot of technologies. It should allow customers to be a part of the development cycle.

To handle those challenges, this paper brings up a reference framework compatible with MBSE principles and tangible building blocks with AI supervision of controller interaction with physics [12]. The control and measurement framework shall facilitate modelling and simulation of multi-physical mechanisms that cannot be grasped without such approach. The envisioned set of R&D[4] activities can be structured as follows:

- to develop advanced *model-based* and *knowledge-based* methods for building digital twins for design, optimization, customization, virtual commissioning and predictive maintenance of machines and robots, using existing and novel data sets [26], [30], [33],
- to develop a *Smart Instrumentation Layer – Layer 1* gathering and processing visual and/or sensor information from supplementary instrumentation installed on the moving parts of the controlled system (*i.e.* at the edge) to enhance the achievable performance and energy efficiency during the whole system lifecycle ([24], [27], [28], [32], [39], [42]),

[1] Computer numeric control
[2] Intelligent Motion Control under Industry4.E - https://www.imoco4e.eu
[3] Artificial intelligence
[4] Research and Development

- to develop modular unified, hardware and software motion control building blocks (BBs) implementing a new condensed edge intelligence, *i.e. Smart Control Layer – Layer 2* ([8], [10], [23], [25], [29], [31], [38], [40], [41]),
- ensure secure interoperability with State-of-the-Art cloud platform, *i.e System Behaviour Layer – Layer 3* and develop specific condition monitoring building blocks providing relevant data for machine digital twins and system behaviour layer, further used either for machine predictive maintenance or re-design, virtual design and optimization; contribute to *open datasets* ([34], [35], [37]).

Finally, it is shown how the methods and building blocks are applied in various industrial domains with different requirements. The framework reflects also key challenges in motion control education [36].

The rest of the paper is organized as follows: Section II describes the common high-level system structure and the overall framework. Section III brings system decomposition to most important sub-components. System IV highlights the main applications where the framework is being tested. Finally, Section V concludes the work and gives pathways towards future developments.

II. Concept and System architecture

Digital twins (DT) can be used for the entire *design* $\rightarrow$ *execute* $\rightarrow$ *change* $\rightarrow$ *decommission* lifecycle of any physical asset. In the past, the role of computing the theoretical behaviour was exclusively fulfilled by simulations. While simulations are still an important and integral part of the digital twins, the purpose of the digital twins stretches well beyond the existing simulation approach. In our work, both the simulations and the digital twins are model based. Such a model describes the theoretical behaviour of the system (including the embedded control algorithms) and its surrounding environment (potentially including human interactions). During the lifecycle of the asset, the amount of knowledge is perpetually increasing. This is because the real-time data acquisition is continuously monitoring, storing and analysing the sensor data of the system. In the project, it is assumed that with this knowledge, the system undergoes a continual improvement process, in one or more of the following ways, *i.e.* based on the analysed sensor data:

- the system engineer is able to improve and refine the model of the system and its environment,
- the system engineer is able to estimate with higher precision the operational states, parameters and outputs of each individual instance of the system; tracking simulators will be employed for this purpose,
- the system engineer is able to predict, optimise and tune the system control algorithms, and hence improve the performance of the system.

In a second stage, given the best-known model and parameters of the system, the digital twin can be used to exploit, simulate and evaluate hundreds of 'what-if' scenarios. These simulation results will support operational decision making at any desirable layer in the system framework (see Fig. 1).

III. IMOCO4.E building blocks and methodology

We have carefully identified the set of building blocks (BB) which create a common umbrella for the majority of applications that were considered (Section IV). Compared to the authors previous works [19], [20], here the BBs are distributed across automation pyramid layers (Fig. 2). This allows to increase the cost-effectiveness of the implementation of smart control algorithms.

A. BB1 – SoC/FPGA platforms for smart control and signal processing

This building block aims to move the high-performance computing close to the deep edge of the system, directly interfacing with the physical signals [42]. Thus, for high-performance applications, BB1 will result in an optimization of the control profile since it will contain application-specific code running in both the FPGA and CPU[5], allowing the offload of some functionalities from the CPU to the FPGA. In such a case, moving digital twins to the edge will enable lower latency, optimized system operations and will better guide the local control. The environment of the digital twins should mirror all these features including a precise and common notion of time that will provide more comparable results to the real system

B. BB2 – High speed Vision in the Loop

BB2 will optimize high speed vision architectures and AI/DT algorithms for the deployment on embedded 'edge' devices (Embedded GPUs, SoC/FPGAs, MPUs, ASICs),[6] with applications in perception, localization, planning, maintenance ([47]). This building block will be deployable as a smart sensor for higher control layers. The key concept is the implementation of low latency and high rate image acquisition, combined with integrated image processing and machine learning towards industrial applications. BB2 is employing some of the AI-based components developed in BB8 and the provided methodologies for training and inference. BB2 could be deployed on BB1.

C. BB3 – Novel sensors (a new type of sensors, wireless communications, self-powered, low-powered)

A key advantage to the rollout of edge processing employing AI will be the inherent potential improvement in achievable system latency [43]. BB3 will make near real-time sensor information available for upper layer AI tasks including machine and deep learning. Whether communication is wired or wireless, signal coding is inevitable, including data (bandwidth) reduction and noise cancelling. This building block deals with the development of control and monitoring tools able to deal with the heterogeneous transmission data

[5]Central Processing Unit

[6]General Purpose Unit, System-on-Chip / Field Programmable Gate Array, Multi-core Processing Unit, Application Specific Integrated Circuit

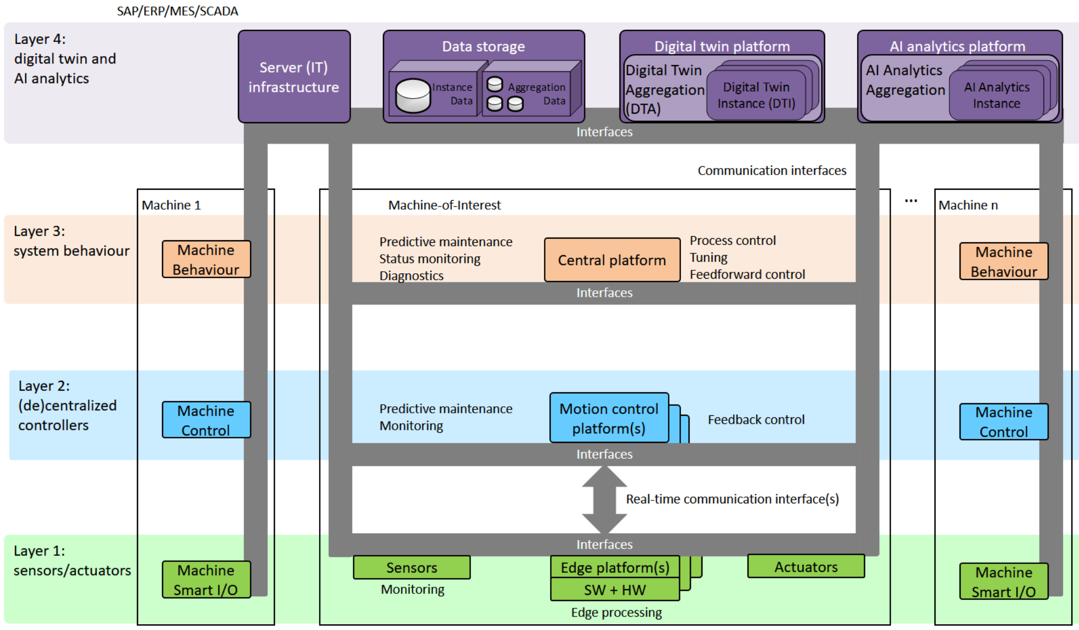

Fig. 1. Proposed concept of digital twin in the control engineer perspective (with DT and AI emphasized)

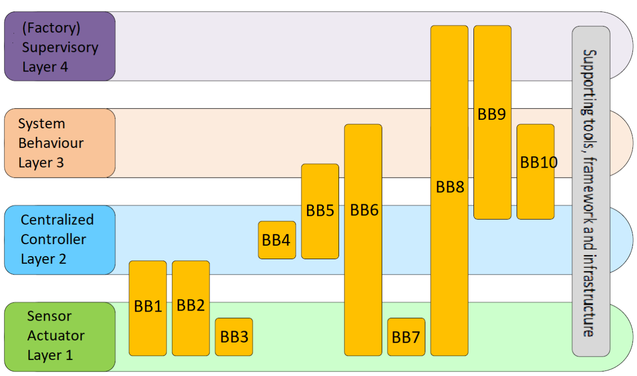

Fig. 2. Building blocks vertically distributed across automation pyramid layers, *i.e.* showing edge-to-cloud intelligence

interconnection with deterministic capabilities. BB3 could be tightly coupled to BB1.

D. BB4 – Real-Time Smart Control Platform

BB4 is an edge component that enables fast and real-time execution of compute-intensive AI workloads [45]. Data can be obtained directly from on board sensors, *e.g.* cameras, or received through low-latency and high-throughput network sensors through real-time fieldbuses (*e.g.* TSN[7], EtherCAT[8]). Data processing will be performed: on FPGA, by *ad-hoc* implementation or soft-core accelerator, *e.g.* Xilinx[9] Deep Learning Processing Units, or on hardware accelerators.

[7]Time-Senstive Networking
[8]https://ethercat.org/
[9]https://www.xilinx.com/

E. BB5 – Smart control algorithms library

BB5 leads to smart control algorithms. These algorithms can be both model-based and data-driven, and build upon reliable knowledge of the dynamics of the system, obtained via physical modeling, data-driven learning (system identification), or both. This same knowledge of the dynamics is the foundation for developing digital twins, simulating the essential behaviour of a system including sensors; in addition, the control algorithms derived in BB5 are absorbed in the digital twin to obtain full closed-loop emulations ([7, 10, 8, 46, 48]).

BB5 algorithms are implemented in efficient (de)centralized processors. Development and validation of algorithms at the simulation level will be implemented through code generation. Algorithm code will be, hence, available for a different set of platforms (BB4 or other industrial controllers). The smart algorithms incorporate in-line learning and other specific AI techniques, including machine learning methods relying on Gaussian processes, to automatically synthesize controllers that push for the highest possible performance of a system.

F. BB6 – Algorithms for condition monitoring, predictive maintenance and self-commissioning of industrial motion control systems

BB6 components will span on all project layers leading from edge to cloud. Data for predictive maintenance sooner or later leads to big data records. They must be significantly reduced to be either stored and successively processed on edge devices or they must be sent to the cloud [Chang et al., 2019], [50]. Computation of condition monitoring tasks like data preprocessing (cleaning), condition indicators evaluation and/or fault detection significantly reduce the burden on vertical communication networks and also on the data storage. AI tasks like machine learning, deep learning, utilization of trained neural networks can ease these tasks while still keeping the effective information in reduced data. AI methods will be used for the automatic commissioning of electric drives and mechatronic systems. AI-based controller parameters optimization and energy efficiency maximization will be targeted.

G. BB7 – High performance servo-drives

This BB will deliver a high performance, highly configurable current amplifier for servo control application. This provides a flexible low-level actuator control in Layer 1 which can be used in high fidelity motion control platforms with stringent performance requirements. BB7 will also provide a virtual counterpart to be ready for co-simulation during all XIL[10] stages of motion control system development, mainly with upper control loops and virtual sensors as well. It is a most-at-the-edge gathering data from physical systems and delivering them to the digital twins synchronization layer. BB7 is not primarily intended for AI implementation (as BB1/BB4), however it will cooperate with related complex algorithms of drive diagnostic. BB7 will be connectable to BB1 and BB4 and will execute parts of smart control algorithms contained in BB5.

H. BB8 – AI-based components

BB8 addresses the manufacturing stage of the product lifecycle management by utilizing AI-based algorithms in developing digital twins for control model development, faults prognosis, diagnostics, deflection modelling of machine structures, anomaly detection and usage-based maintenance [44]. Digital twin creation and development require extensive knowledge of different technologies.

The developed AI-algorithms target multi-modal data (*e.g.* vision, audio, pressure, feedback signal) to increase productivity by applying modern reinforcement learning techniques for the development of control models which bare potential for fast reconfiguration of the production line.

I. BB9 – Cyber-security tools and trustworthy data management

BB9 will ensure to deploy all the necessary cyber security mechanisms (i) with respect to real-time synchronization and communication with digital twins and (ii) in the operation of the complex digital twins' systems. BB9 will provide cyber-security technologies facilitated by AI-based anomaly detection mechanisms; it will also exploit federated learning approaches (AI edge-to-cloud deployments) to ensure multi-level cyber-security assurance.

It will provide secure and trustworthy data management aggregated from perception sensors (BB2), novel sensors (BB3) and exploited by FPGAs (BB1), by the real time smart control platform (BB4), and the high-performance servo-drives (BB7). Moreover, it will facilitate fast and secure accessibility to data for the AI components (BB8) and algorithms (BB5, BB6).

[10]X-in-the-Loop

J. BB10 – Motion / path planning, collision avoidance and navigation algorithms

BB10 will ensure mode- and learning-based path and motion planning of mobile as well as manipulator robots. This building block will also enable the algorithms to be tested, evaluated and improved in a digital twin of the environment where the robot is operating. In complex digital twins, BB10 has strong interoperability with BB5 and BB6.

BB10 will use machine learning approaches to ensure fast data stream processing from multi-sensory sources to capture changing environments in real-time as the basis for spatial mapping, obstacle detection and machine decision-making. Advances in deep reinforcement learning for robot motion planning [Long et al. 2017] are analyzed and implemented. Interoperability with BB3 and BB8 is given.

IV. Selected pilot applications for verification

In this section it is shown that the framework developed has a potential applications in diverse technological domains (Fig. 5).

A. Pilot 1 – 3D printing

Pilot 1 is an 'affordable' industrial-grade 3D plastic filament printer with automated material handling, tool exchange and thermal conditioning. Reliability and predictability of performance (mainly accuracy) are of particular importance for the industrial application of the printer. The printing process occurs at relatively high temperatures, which is challenging for print accuracy. The thermal load acts as a large disturbance on the positioning systems and causes warpage of printed objects. Furthermore, the accuracy of the deposition process and filament flow inside the printer nozzle is a complex physical process depending on both temperatures, pressure and motion profiles and therefore challenging to control and optimize.

B. Pilot 2 – Semiconductor production

This machine is a platform for high speed and high volume semicon manufacturing. The machine is a part of the whole production line, hence predictive maintenance is of high importance. The main problems which must be solved are: to improve motion accuracy; to ensure predictable performance across multiple machines and to optimize the whole process.

C. Pilot 3 – High speed packaging

The high-speed packaging machine represents a full production process. It is composed of a lot of components, like feeding station, strip buffer, sterilizer, liquid filling, cutting chains, *etc*. The aim is to improve the current machine monitoring and to improve the actual quality of the control process.

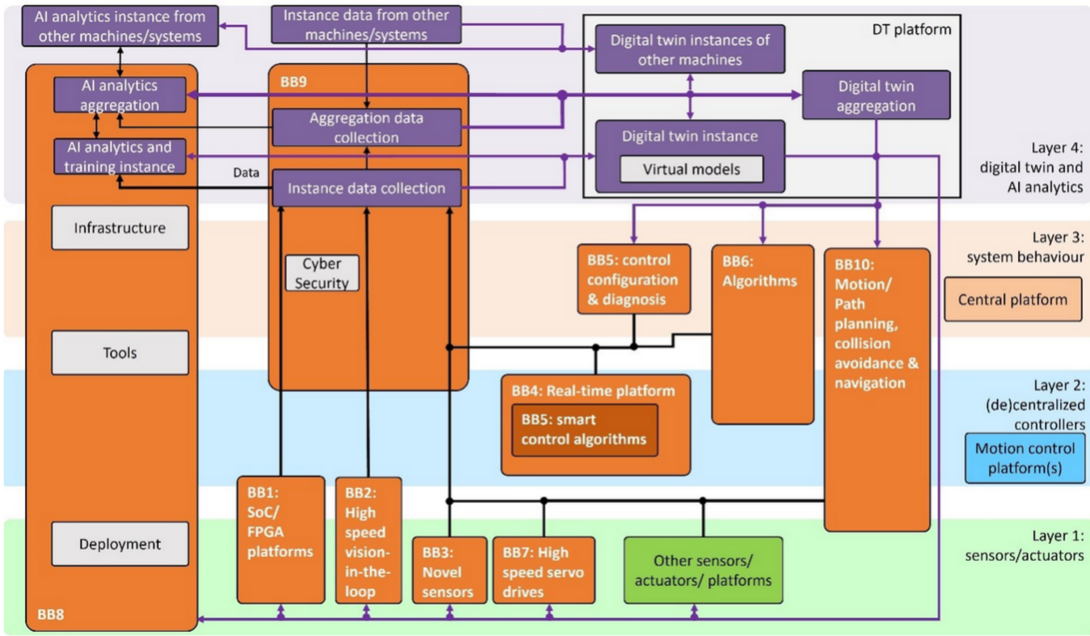

Fig. 3. Digital twin view point with BB interactions; vertical distribution across automation system layers.

D. Pilot 4 – Healthcare robotics

The healthcare pilot is intended to provide treatment like image-guided therapy. The long-term goal is to increase imaging flexibility *via* a more complex kinematic structure and smart control. The key problem is also to extend system monitoring and enable fast improvements and testing. Finally, system maintenance and service should be improved using state-of-the art data model technology.

E. Pilot 5 – Mining / tunneling robotic boom manipulator

Robotic boom manipulators are the enabling technology for autonomous underground processes. Project technologies are piloted in at least digital twin of a mining / tunneling robotic boom manipulator on a carrier where feasible. The main technological requirements are machine vision/sensor algorithms to enable semi-autonomous and autonomous operations; collision avoidance methods for autonomous and semi-autonomous boom control and path planning; the added value of data and technologies in business (AI, digital twins, task planning).

We would like to point out that besides the main pilots, the IMOCO4.E project verifies the framework also on demonstrator applications in shaver blades production, plastic molding, warehouse logistics and cosmetic production ([49]).

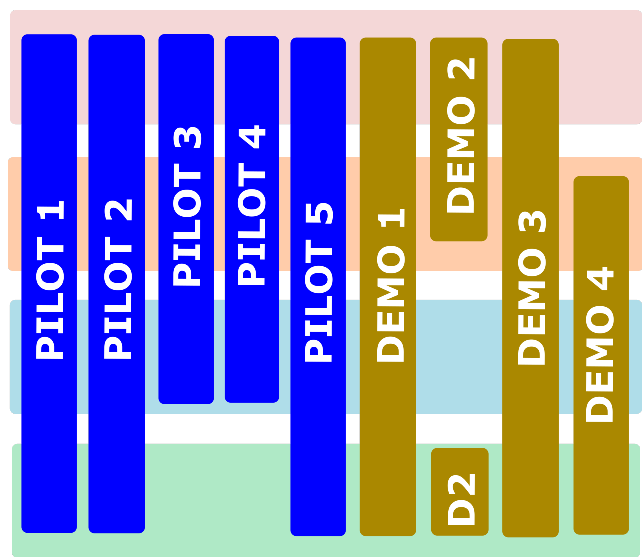

Fig. 4. Pilot and demonstrator applications distribution across individual automation system layers.

V. Conclusions and Future Trends

It was shown that machine performance optimization and their smart maintenance need an integral framework of various technologies (HW, SW, sensory, communication, data storage and analysis, etc.). When dealing with the whole machine lifecycle advanced digital twin principles and data analysis methods must be employed. Finally, diverse pilot application were analysed in different application domains (semicon, CNC machining, packaging, 3D printing, medical manipulators and others). We have analysed the full vertical chain of the automation pyramid with special focus on digital twin implementation and employment of AI methods wherever it brings benefits.

Apparently, there is an extraordinary motivation to continue in cooperation also under the future Horizon Europe framework programme, e.g. to make the whole process service-based and allow also other partners to become part of it easily.

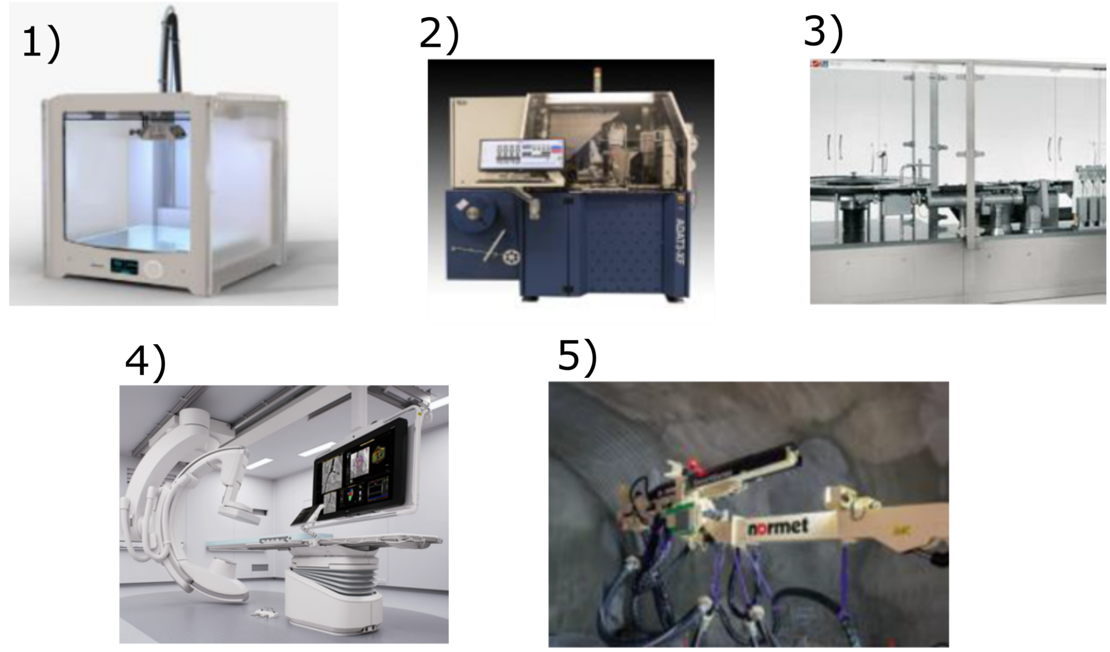

Fig. 5. Pilot applications: 1) 3D printing; 2) Semiconductor production; 3) High speed packaging; 4) Healthcare robotics; 5) Mining / tunneling robotic boom manipulator

TABLE I
IMPLEMENTATION OF BBS ON DIFFERENT PILOTS – TECHNOLOGICAL MATRIX; Y = BB WILL BE IMPLEMENTED, – = BB IS NOT RELEVANT

BBs pilots	1)	2)	3)	4)	5)
BB1	Y	Y	–	–	–
BB2	Y	Y	Y	–	Y
BB3	–	Y	–	Y	–
BB4	Y	–	Y	–	Y
BB5	Y	Y	–	Y	Y
BB6	Y	Y	Y	Y	–
BB7	–	Y	–	–	–
BB8	Y	Y	Y	Y	Y
BB9	Y	–	Y	–	Y
BB10	–	–	–	Y	Y

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