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RESEARCH ARTICLE

# Sustainable Hyperautomation in High-Tech Manufacturing Industries: A Case of Linear Electromechanical Actuators

**MIKHAIL E. FEDOSOVSKY[1], MIKHAIL M. UVAROV[1], SERGEY A. ALEKSANIN[1], ANTON A. PYRKIN[2], ARMANDO WALTER COLOMBO[3], (Fellow, IEEE), AND DOMENICO PRATTICHIZZO[4], (Fellow, IEEE)**

[1]Diakont SRL, 52046 Lucignano, Italy
[2]Control Systems and Robotics Department, ITMO University, 197101 Saint Petersburg, Russia
[3]Hochschule Emden-Leer, 26723 Emden, Germany
[4]Department of Information Engineering, University of Siena, 53100 Siena, Italy

Corresponding author: Mikhail M. Uvarov (uvarov@diakont.com)

**ABSTRACT** Hyperautomation is a promising but sparingly implemented concept in intelligent manufacturing. One of the reasons for the suboptimal adoption of hyperautomation is the large gap between current theoretical frameworks and practical methodologies and tools that can be applied in a real industrial production scenario. This situation has become much more complicated in high-tech enterprises, which face a particular set of issues in terms of innovation, cost-effectiveness, and supply chain management in today's globalized environment. This manuscript provides a new conceptual business framework and technological background for achieving sustainable hyperautomation in the manufacturing of linear electromechanical actuators (LEMA), a key component of several cyberphysical actuators. A set of digital tools and innovative concepts, such as intra-enterprise 3-level factory and definitive designs based on unified solutions, which enable mass customization and offer up to 1000 variants of the LEMAs, are introduced to achieve synergistic interaction between different business functions and provide significant cost and technological advantages. To make manufacturing more customizable, a modular design approach is used, and simultaneously, to facilitate mass production, the focus is given on roller screw transmission modules, representing approximately three-fourths of the added value of LEMA. Furthermore, the concept of synergetic forward integration is proposed and explained using an example of robotic resistance spot welding. This framework involves a closed loop of industrial mature digital tools that enables autonomous product design and manufacturing via Responsive R&D (Research and Development) and feedback-driven dynamic interactions with the market and production system. These steps allow intelligent and automatic decision making throughout the digitally connected systems within the company and out of the company through a digital networked connected intra-enterprise world inside the supply chain with minimal human intervention.

**INDEX TERMS** Hyperautomation, mass customization, digital twins, responsive R&D, industry 4.0.

## I. INTRODUCTION

The seamless integration of production and operations with digital technologies is the central feature of the Fourth Industrial Revolution (I4.0) [1], [2]. I4.0 bridges the physical and virtual worlds and places great emphasis on smart manufacturing practices that involve a feedback-driven dynamic network of digitally interconnected machines, devices, sensors, and people. The large amount of data collected through this interconnected network enables responsive and automated decision-making and control. These strategies can significantly enhance industry competence;

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however, successful implementation of digitalization warrants a significant change in business structure and practices [3], [4].

Smart manufacturing is highly dependent on cyberphysical systems (CPSs) and digital twins (DTs). In CPSs, the physical system consists of asset / things that provide or collect real-world information and transfer it to cyber systems able to process it (in edge as well as in cloud) for itself and / or for the rest of the network [5], [6], [7], [8]. Moreover, the Cyber systems are computational modules that analyze gathered data in real-time and notify the findings of the corresponding physical systems through multiple feedback loops. On the other hand, they are digital representations of assets, processes, or systems [9], [10], [11]. DTs can be integrated with artificial intelligence, machine learning, and cognitive services to optimize and automate production. DTs can cover the entire life cycle of an asset or process by forming a closed-loop chain for smart connected products, services, production and logistics [12]. The concept of hyperautomation has recently been introduced in pursuit of complete automation. Hyperautomation is an all-encompassing automation that employs artificial intelligence, machine learning, and other advanced techniques. Gartner defined hyperautomation as a disciplined business-driven methodology that businesses employ to quickly discover, validate, and automate business and IT activities. Although robotic process automation (RPA) was once the mainstay of hyperautomation, a variety of technologies are currently in use [13], [14]. According to Gartner, this is the most important technology trend in 2020 [15].

Rapidly changing consumer preferences, technological advances, and market dynamics make it necessary for high-tech industries to embrace persistent innovation. Globalization has increased competition, leading to a systematic decline in the prices of high-tech products. Only businesses that innovated their business models to meet the requirements of a globally competitive and innovation-driven market have survived. The turbulent economic environment also adds an unpredictable variable to this complex process, making it necessary for the manufacturing process to adjust quickly to the prevailing market demand. I4.0 aims to address some of these concerns by making manufacturing more agile, cost-effective and technologically superior [16], [17]. The concept of I4.0 presupposes the active use of digitalization, including the development and improvement of decision support systems for product development and production that can respond rapidly to changing customer requirements [18]. Being disruptive in many ways, I4.0 makes it necessary for industries to critically evaluate all aspects of the value chain and design new and adaptive business frameworks [18]. In fact, I4.0 has blurred the lines between technology and management, and emerging digitalization trends have disrupted traditional business models [19]. Although hyperautomation has been shown to have great potential in various studies, there is a lack of consistency in the literature on mass-customized or "demassified" production, particularly in the context of sustainable hyperautomation in the high-tech industry.

Electromechanical actuators (EMAs) are integral components of CPSs used in various industries. With the growing trend towards automation and robotics, the demand for EMAs is expected to grow. However, because of stiff competition in this segment, there has been a substantial reduction in the market price of EMAs. Recent economic crises have adversely affected market dynamics. In the context of decreasing demand, falling market prices, and technological advances, sustainable and intelligent manufacturing of EMAs is only possible by developing a reconfigurable production line for mass customization in small and medium batches, while maintaining technological superiority and production costs comparable to mass production.

Automating manufacturing using integrated DTs and predictive models allows for iterative real-time product and production process optimization. However, technical complexity, innovation challenges, rigidities caused by external and internal systems, and turbulent market dynamics pose a substantial barrier to high-tech industries achieving successful digitalization and automation [20], [21]. Furthermore, although digitalization has received great interest in scholarly research and managerial practices, there is limited understanding of the comprehensive business framework that can be applied to achieve hyperautomation in high-tech manufacturing firms. Indeed, even in industries where CPSs and other digital tools have been implemented, to the best of the authors' knowledge, automation objectives have only been partially realized, and there is no prior study reporting a business framework for hyperautomation in a high-tech firm.

The term "de-massified production" was first used in 1980, and in 1993, the concept of mass customization was introduced [22]. In 1995, a description of the structure of a decentralized enterprise appeared [23]. Wang *et al.* proposed a framework to bridge the gap between mass ñustomization and mass personalization using I4.0 technologies [24]. Specifically targeting intermediate product configurations that are neither generic nor standardized, Song *et al.* proposed an uncertain decision-making model for mass personalization of production within I4.0 [25]. These authors presented the theoretical foundations and practical implementation of an assembly system for high-tech products, using the principles of standardization and redundancy. Mourtzis *et al.* presented a web-based support platform for mass customization and personalization [26]. The platform is responsive and allows interaction with customers during the product design phase. The proposed solution was integrated with a decentralized manufacturing platform implemented using web technologies. In a recent study, Lee *et al.* demonstrated the feasibility of an OrderAssistant system that generates product specifications from customers' voices [27]. To maximize customer satisfaction, the authors used the Kano model and various optimization methods. The resulting characteristics were transferred to a top-level decision support system that allowed for the simultaneous design of a new product configuration and a change in the production cycle.

Recently, significant attention has been paid to the reconfiguration and optimization of assembly production using a late customization approach [28]. Rossit *et al.* presented a framework for reconfiguring the assembly line sequence in the final stages of production depending on the requirements of the customer [29]. It was suggested that the framework be implemented as an interactive online system for setting the order parameters. This approach of analyzing customer requirements allows a sufficiently high level of personalization of finished products while maintaining the production level according to the changing production environment. Bednar and Rauch developed a mathematical model to generate various configurations of a manufactured product based on a combination of assembly units, which can be used as an auxiliary tool to quantify the complexity of implementing mass customization projects [30]. However, the model was self-contained, did not support end-user feedback, and did not consider market conditions. Trstenjak *et al.* proposed that process planning, sequencing, and scheduling are the three areas of production planning that must be implemented using the key technologies of hyperautomation [16]. These authors presented a new conceptual model of the planner that uses big data, complex mathematical software, predictive algorithms, and client feedback to make planning decisions, theoretically making it possible to completely remove human intervention from this process. However, the article lacks details on the business requirements and conditions under which the practical implementation of this approach would be possible.

Outlining the challenges associated with traditional centralized scheduling models, Zhang *et al.* reviewed more than 100 research papers to identify traditional scheduling methods that can be easily combined or transformed into smart distributed scheduling [30], [31]. The emergence of big data and artificial intelligence has brought new insights into innovation in decision support systems (DSS) [32], [33]. The main impact and key aspects of these smart systems are the product lifecycle approach and the use of DTs. For example, an effective DSS can be built using a set of digital tools to describe and model a product and its production processes. This is also termed the DT of production facilities and involves collecting, storing, and using data at all stages of the decision-making cycle. The methodology for calculating metrics of the complexity of the production of customized products has also been recently implemented in a real enterprise that manufactures laser-processing equipment [34]. It was also shown that the proposed approach could support the decision-making process at the strategic level of the company by quantifying the complexity and obtaining additional significant information for the selection of products and services that can be developed and offered to customers. However, the presented methodology did not involve software implementation; therefore, at the current stage, it cannot be used as an automatic decision-making module of an intelligent enterprise management system. These metrics are also calculated based on a survey of enterprise managers and experts and do not consider feedback from the market.

Recently, Grassi *et al.* [35] proposed a semi-heterarchical manufacturing planning and control architecture. Based on this architecture, the production management model can dynamically distribute assignments according to various dispatch rules based on the queueing theory. The performance of the model was evaluated for various production scenarios using hybrid modeling systems. Modeling was carried out exclusively for the shop floor, but the authors claimed that the methods under consideration could also be applied to dynamic dispatching at other levels of enterprise management. It is also worth noting that the developed planning algorithms did not consider feedback from the market.

Going beyond of what is currently known, this paper presents a comprehensive account of a sustainable hyperautomation approach describing the application of a novel methodology for achieving hyperautomation in manufacturing of LEMAs within cyberphysical production systems. The business framework, associated to the hyperautomation of the LEMA production relies on responsive Research and Development, mass customization and use of DTs for Industry 4.0-compliant reconfigurable products, production processes, production control and management, and added-value services for intra- and inter-enterprise businesses. Table 1 compares the properties of frequently reported hyperautomation approaches with the framework provided in this study for sustainable hyperautomation, highlinghting the differences and the novel aspects introduced in this manuscript.

At this point, it is important to reinforce the fact that the applicability and particularly the impact of the hyperautomation approach discussed in this paper has been validated based on the real experience with hyperautomation implementation at Diakont premises, a prominent multinational corporation that develops and manufactures a wide variety of high-tech goods in different regions of the world [36].

Following this introductory section that includes a brief literature review addressing relevant reported related works, Sections 2, 3, and 4 introduce and develop the novel hyperautomation components. In these sections, after providing the major characteristics of the business framework, the technological background for achieving sustainable hyperautomation in the manufacturing of LEMAs is presented. A set of digital tools and new concepts, such as intra-enterprise 3-level factory and definitive design-based unified solutions that allow mass customization and provide over 1000 LEMA variations, are also described. These novel techniques promote synergistic interactions across many business functions while providing considerable economic and technological benefits. The complete framework, based on the application of the DIN Specification 91345 RAMI4.0, as it has been codified and effectively implemented in the Diakont industrial system, is described, together with an explanation of the research methodology, in Section 5. Section 6 discusses the impact and mainly favorable effect of the hyperautomation method on production costs and overall return on investment. Finally,

**TABLE 1. The key difference between state-of-the-art hyperautomation and the approach developed in the current research.**

| Key aspects | State-of-the-art of Hyperautomation | Sustainable Hyperautomation Approach |
|---|---|---|
| *Technologies used* | RPA<br>Process Discovery<br>Process Mining<br>iBPMS (Intelligent Business Process Management System)<br>Low-Code<br>Business Rules Engine | RPA<br>Process Discovery<br>Process Mining<br>iBPMS (iEMS (Intelligent Enterprise Management System))<br>CRM (Customer Relations Management System)<br>PLM (Product Lyfecycle Management System)<br>Low-Code<br>Business Rules Engine<br>Integrated Data Bus<br>Mathematical and Economic Modeling and Optimization |
| *Data Sources* | Mostly documents and data gathered through iBPMS to perform RPA and operative costs reduction | Data gathered through iBPMS, CRM, PLM to perform strategic forecasting, optimization, RPA and operative costs reduction |
| *Processes covered* | Operational processes: manufacturing execution, payroll, accounting, service desks, direct sales | Full scope of the processes, including: market evaluation and demand forecasting, requirements to the product, product design, manufacturing process design, managing process design, strategic and operational planning and scheduling, manufacturing execution, including all the operative primary and auxiliary processes |
| *Interconnection* | Mostly local separated processes | All the processes influencing one to the other through Integrated Data Bus and models in real-time |

Section 7 presents the conclusions and projections for the future.

## II. LINEAR ELECTROMECHANICAL ACTUATORS: TECHNO-ECONOMIC FEATURES

### A. TECHNOLOGY

Linear electromechanical actuators (LEMAs) are used to convert electrical energy into linear mechanical force [37]. The generated mechanical force can be used in different applications where the controlled physical movement of an object is required. LEMAs are widely used in applications such as welding and pressing [38], [39], production of plastic and rubber items [40], [41], dosing and packaging of food and pharmaceuticals, mechanisms in shipbuilding [42], managing fuel flow in turbines and geometry of aircraft engines [43], [44], [45], control of valves in the power industry, robotics and manipulators [46], [47], and testing and simulation. A distinctive feature of modern LEMA is its ability to function strictly according to the required operation cycle and provide precise data at any given moment, making it a valuable component of modern cyberphysical systems for automation and robotics. Three main types of gears were used [48], [49]: lead screws, ball screws, and roller screws. The roller screw gear is a relatively recent development in LEMA technology. Owing to its high efficiency, wear resistance, and load capacity, LEMA with roller screw transmission types is the most suitable for applications that require high force, speed, and service life. Further details of the roller screw technology developed by the authors can be found elsewhere [50], [51]. The following discussion is centered on a specific example of hyperautomation in the manufacturing of LEMA with Roller Screw Gear (RSG); however, the core concepts of the hyperautomation framework presented in this manuscript have also been employed by authors in the manufacturing of components of CPS, such as feedback sensors, servo drives, and electric motors.

### B. MARKET PRICE AND PRODUCTION COST

The market for LEMA has grown in the recent past, and is expected to grow further. However, increased competition and economic crises have reduced the market prices of LEMAs to unexpectedly low levels. The prevailing market prices are much lower than the forecasts for different periods. Taking the example of LEMA with roller screw transmission for spot contact welding, Figure 1 illustrates the actual market price, forecast market price, and target production cost [52], [53], [54]. In 2012, the market price was EUR 4500, and the market forecast indicated that the price would decrease for approximately 15% and stabilize in the coming years. However, the market price followed a markedly downward trend compared to the expected price, forcing industries to review their target costs significantly in 2017. In turn, the reduction in the target production cost makes it necessary to revise the product design and production process. In particular, the market price for 2012 allowed the manufacturing of customized products in small and medium batches and offered additional technical advantages to the product, such as longer service life and an integrated system of lubrication replacement. In 2015, the business landscape changed remarkably with the arrival of Asian manufacturers, forcing European and American car manufacturers to reduce their costs. This development led to a further reduction in the market price of LEMA as part of the spot welding equipment [55]. Since price is the primary factor affecting consumer decisions, the presence of additional characteristics such as an increased life cycle and additional features ceases to be a competitive advantage, and a customized product with technological superiority over competitors is the only means to sustain the competition. With a current target cost, which has decreased by 2.5 times, the unified modular design of LEMA using reconfigurable assembly lines and integrated automation and digitalization of the production cycle is a plausible means to remain competitive. The next section describes the

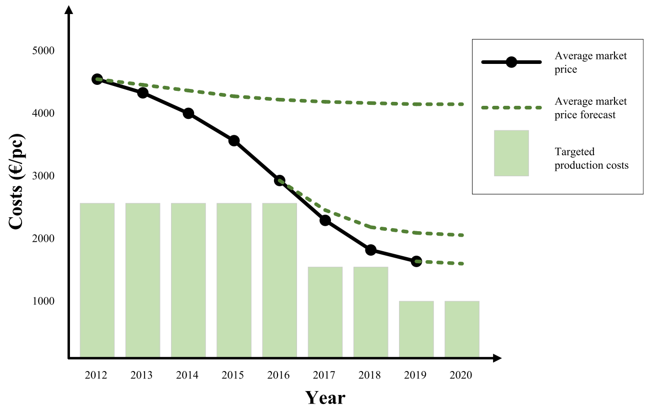


**FIGURE 1.** Dynamics of the spot contact welding LEMA average market price and targeted production costs, Diakont data [36].

conceptual and analytical framework for achieving hyperautomation in the sustainable manufacturing of LEMA.

## III. SUSTAINABLE HYPERAUTOMATION

### A. DEFINITION

In this study, sustainable hyperautomation is defined as the feedback-driven system-wide automation of business, providing an autonomous response under different business cycles and diversified customer requirements. A digital representation of a real-world entity or system is defined for the aim of this work as DT. The purpose of DT is to analyze a product or system, predict how it will function, and optimize its effectiveness and workflows throughout its lifecycle. Responsive R&D is defined as the iterative optimization of the product design and production process to provide a cost-effective and technologically superior solution in different scenarios. Intelligent manufacturing is defined as a manufacturing process that autonomously optimizes and applies the best possible technological and cost-effective solution under given circumstances depending on customer requirements and market dynamics. Essentially, sustainable hyperautomation is supported in the approach described in this paper by usage of mathematical modeling and digital tools for Responsive R&D, DT testing of real-world data, demand forecasting and cost optimization, and autonomous decision-making. This approach, as described in the next sections, is leading to synergistic interactions across different business functions within the company and out of the company through an intra-enterprise and supply chain infrastructure.

### B. DESCRIPTION OF THE COMPANY

The framework discussed in this paper is based on the practical experience of implementing sustainable hyperautomation at Diakont. Diakont is a prominent multinational corporation, a group of high-tech manufacturing companies from the European Union and the United States that designs and manufactures a wide variety of high-tech goods all over the world [36]. For the past 12 years, Diakont has been involved in the design and manufacturing of safety and enabling technology products for the power and manufacturing industries.

The following methodology is based on Diakont's experience in achieving successful hyperautomation for sustainable manufacturing of LEMAs at Diakont premises in Lucignano, AR, Italy.

### C. SYNERGISTIC FORWARD INTEGRATION USING A SMART TOOL

One of the key aspects of sustainable manufacturing of LEMAs is identifying areas that can offer synergistic advantages. In several scenarios, manufacturing a complete CPS rather than just LEMAs can provide a synergistic advantage in terms of cost and technical quality. For example, the CPS involved in robotic resistance spot welding consists of several components, including an industrial robot, a welding gun with electrodes, and LEMA that controls the gun during welding. Analysis of the system reveals two tasks to be solved: the first is the delivery of a welding toolset to the welding point using an industrial robot, and the second is the primary technological cycle of welding performed by the welding gun and actuator. While the first task is auxiliary and can be performed by any five- or six-axis industrial robot, the second task is critical and impacts the performance and quality of the entire process. The technological setup that implements the primary welding cycle is currently not independent of CPS. The control of the welding cycle was assigned to the control system of the robotic arm, which sent a signal to the welding current controller to perform welding and control the actuator that provided the closure of the gun with a given force. The required timing diagram of the force is provided by either the servo drive of the robot or a separate actuator servo drive. Any type of architecture implies certain restrictions caused by the need for motor feedback: the robot controller may not interact with any external servo drive, and the robot servo drive may not interact with any sensor. Thus, it is advisable to create a ''smart tool'' as a separate CPS that would implement the primary technological cycle of welding, an additional ''7th'' axis of an industrial robot.

Such a system consists of an actuator, position and force sensors, a control device implementing the functions of a controller, and a servo drive that will be integrated with the welding controller [56], [57]. The advantages of such a system include independence from the industrial robot that is needed to deliver the tool to the welding point and simplified interaction with an industrial robot. It sends a signal that the necessary position is taken and that the welding can be started and receives a response, which means that the welding cycle is completed. This decentralized control approach is particularly relevant for upgrading existing welding lines when the robot has already been defined, and before that, a pneumatic solution was used as a gun actuator. The price advantage of the integrated solution over the currently used analogs is the use of a less expensive and designed specifically for this application ''smart device'' (controller and servo drive), which does not have redundant features. Furthermore, the addition of extra sensors and a signal processing unit to this new CPS enables additional functionalities such as online diagnostics and predictive maintenance. This allows real-time optimization of the welding process, resulting in reduced welding line downtime, reduced power usage, and a positive environmental impact.

This synergistic forward integration not only brings agvantages to the industry and customers, but also increases the prospective demand for the LEMA as a part of this new CPS.

### D. INPUTS FOR INTELLIGENT MANUFACTURING

The first step toward attaining sustainable hyperautoma- tion in the manufacturing process involves developing an algorithm for accurate demand forecasting and estimating commensurate output numbers [58]. Essentially, the volume of production and product variability are the most important elements to consider when deciding on product development and management [59]. Other elements to consider when automating the production process include product design manufacturing technology, and the organization of the production process.

Based on the current market dynamics and with a focus on the areas in which the company has a competitive advantage, an intelligent demand forecasting approach has been developed. In this context, a model of calculation, analysis, and optimization of financial-economic parameters of production (MCOFP) has been created by Diakont that allows forecasting based on accurate information obtained from current market dynamics (sales volumes, trends, and competition). Additionally, the model considers the unique opportunities offered by the company, in addition to customer relations management (CRM) input. The forecasting process using these digital tools begins even before the product is conceptualized and designed. It is essential to reinforce, at this point, that starting a new business from estimating possible demand, sales and production volumes is a commonly used approach. However, one of the novelties of the hyperautomation framework described here is the use of an adequate mathematical modeling of the market, designed and implamented as a piece of software, integrated as economic model of the production system into the automation and management infrastructure of the company. Once information on the targeted production cost and projected sales volume is available, R&D for product development and production begins. The successful implementation of responsive R&D is also made possible by this method, which allows for the prediction of the impact of each decision made as well as the forecasting of changes in product cost.

### E. RESPONSIVE R&D FOR PRODUCT DEVELOPMENT AND MASS CUSTOMIZATION

Because LEMAs are used in diverse applications, the technical specifications and design parameters generally have a broad range. Therefore, product design and production processes must be flexible [60]. This requires responsive R&D that is well-integrated with different manufacturing steps, allowing quick customization and delivery of LEMAs with desired specifications without adversely affecting the production cost, time, and technical features. Rather than focusing on the composite design of LEMAs, in the hyperautomation approach used at Diakont, the design and engineering stage of integrated R&D begins by identifying the common components of different types of LEMAs. Furthermore, achievable sales and production volumes are regularly updated based on the new information received from the market analysis or from within the company. Technical analysis of the LEMAs revealed that roller screw transmission is the key element for all types of LEMAs. Therefore, the focus was on developing a range of roller screw designs that cover the technical specifications desired for various applications. As a matter of fact, the form in which the unification of the product / production design goes, in connection with the new information received from the marked, provided to and from the company engineering department, in a digitalized and interconnected management information system is enhancing the novelty of the hyperautomation approach.

Once the designs are ready, the next stage of R&D is to determine the optimal manufacturing technology to produce roller screw components with the advantages of flexibility, versatility, and performance over conventional manufacturing technology. The entire range of products that can be manufactured using the common key element is allocated to a single class of devices based on common principles. The modular design concept was implemented using common design and technological solutions (Figure 2).

As a matter of fact, the Responsive R&D addressed here above means not only ‘‘responsive to the marked change’’, but also means ‘‘interconnected’’, because through this R&D not only a product is developed, but also the process technology and methods for the production organization are designed, which are supported by the result of the analysis provided by the MCOFP. The concept of Repsonsive R&D is novel by itself, including into R&D not only problems and tasks of the product design, but technology, process, factory building, equipment and processes, as well as support to automation and management decision making processes.

Three basic unified modules – the roller screw, the rotor, and the stator make up to 75% of the added value of the product and that do not require changes during the development of a new product or product customization. The unified design includes 20 different variants of fastening and connecting elements, 4 dimension types, 6 types of feedback sensors for actuator control, and 6 external options, providing the possibility of creating up more than a thousand variants of the final product. Upgrading the product with properties not provided for in the basic universal design can be carried out in the process of minimum customization (refinement) of additional parts and can be implemented in a short time with minimal cost. This approach resulted in a low cost of production owing to the mass production of basic unified modules, and it allowed the use of high-performance manufacturing technologies, such as thread whirling, circular grinding using

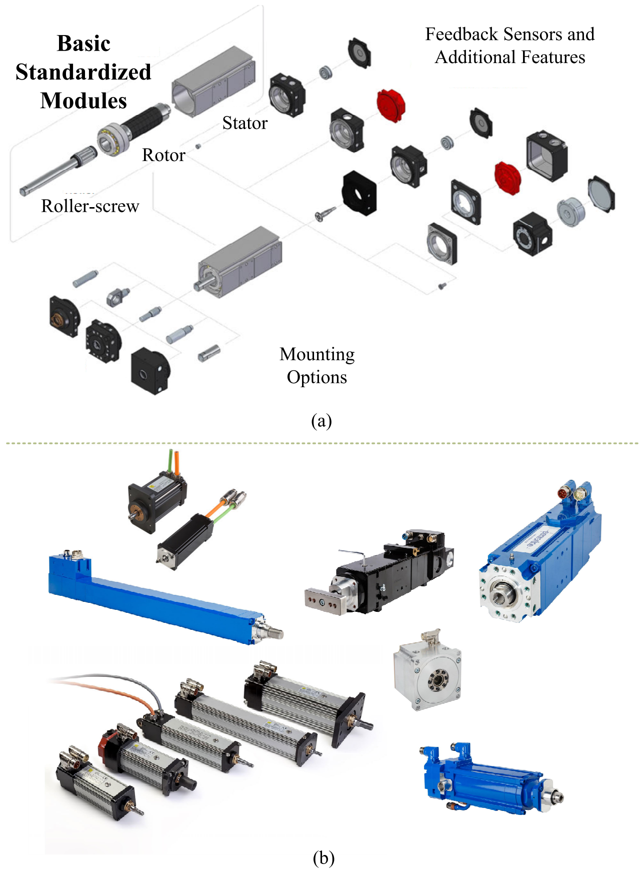


**FIGURE 2.** Unified linear motion actuator scheme (a) nd a line of customized products (b).

**TABLE 2.** Distribution of tasks in the concept of "three-level factories".

| Level 1 factory | Level 2 factory | Level 3 factory |
|---|---|---|
| • Manufactures standard unified parts of off-the-shelf products<br>• Purhases the materials for production of standard unified parts of off-the-shelf products<br>• Inventory model of standard parts of off-the-shelf product assemblies<br>• Purchases non-manufactured components to deliver to factories of levels 2 and 3 in case of economic feasibility | • Produces standard unified sub-assemblies<br>• Purchases non-manufactured components for unified sub-assemblies<br>• Inventory model of standard parts and unified sub-assemblies to ensure uninterrupted supplies to the factories of level 3 | • Assembles and tests off-the-shelf products<br>• Sales and ships off-the-shelf products<br>• Performs customer service<br>• Purchases non-manufactured components for off-the-shelf products<br>• Inventory model for standard parts and sub-assemblies<br>• Produces, including cooperation, unique non-standard parts |

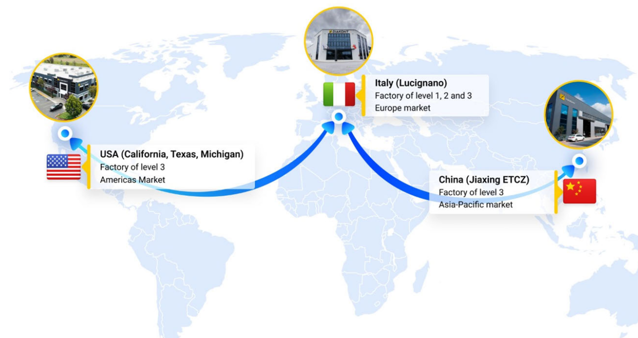


**FIGURE 3.** Geographically distributed operations network in "three-levels factories" concept created by Diakont [36].

a Cubic Boron Nitride (CBN) tool, and ion-plasma nitriding for metal hardening, leading to a superior quality product. It should be noted that the high-performance manufacturing technologies mentioned above have low techno-economic feasibility for small-scale production.

### F. GEOGRAPHICALLY DISTRIBUTED SUPPLY CHAIN

To reduce the delivery period and provide services rapidly, a geographically distributed supply chain business model was designed according to the original concept of "three-level factories" generated at Diakont. In this approach, tasks are distributed among different factory levels, as shown in Table 2 and Figure. 3 [61], [62], [63], [64]. The factories of the first two levels produce standard parts and standardized assemblies in large batches. Third-level factories assemble, test, package, and ship finished products to customers. It has a warehouse with unified components at the minimum required volume. Additionally, third-level factories provide product services and support in geographical proximity to customers. Shipment from the third-level factory eliminates the time spent on transportation and customs clearance. In addition, third-level factories serve as centers for the localization of assembly components. The procurement of components from domestic markets or cooperative manufacturing stimulates domestic markets and provides cost advantages for several components. Figure 3 shows the geographically distributed production and supply chain created by the Diakont. One of the key tasks in the concept of "three-level factories" is to provide rational inventory management, which would ensure the minimum amount of goods necessary to maintain production under unstable demand conditions.

The real implementation of the "three-level factories" concept, where the production system is considered as a combination of 3 different logic levels, physically combined or not, inside one integrated (digitalized and networked) management and supply chain system, allows, among others, a real-time and visible presence for the customer, shortening and optimizing schedules / terms and lower costs. This is rather novel and is an essential requirement to be fulfilled by the hyperautomation framework.

Such a distributed supply chain allows the company to position its production and business infrastructure within the "Connected World" level of the DIN SPEC 91345 RAMI4.0 [2]. This, as a major consequence, facilitates the Industry

4.0-compliant digitalization of such infrastructure supporting the successful implementation of the hyperautomation framework.

## IV. HYPERAUTOMATION SUPPORTED BY A CLOSED-LOOP SYSTEM OF DIGITAL TOOLS AND INTELLIGENT ENTERPRISE MANAGEMENT SYSTEM

Intelligent manufacturing of high-tech products requires integrated R&D and prompt decision-making regarding optimal product design and optimal production processes. For sustainable hyperautomation, it is necessary to develop a set of digital tools that allow testing solutions on interconnected mathematical models, assess the mutual influence of various external and internal factors, and create effective corrective measures autonomously. Furthermore, to ensure the adaptive manufacturing of CPS/EMA in Diakont, a novel system of seamlessly integrated DT has been developed that dynamically interacts with the market (Figure 4). The system consists of three key blocks. The first block involved the DTs of the product and production process.

These DTs are used to design the product, promptly verify the product parameters at the development stage, and autonomously choose an optimal manufacturing technology that provides a customized product with minimum adjustments in the production process, resulting in minimal prime cost and production time [65], [66], [67], [68], [69]. It should be noted that although solutions for individual purposes and stages are well known [9], [70], [71], [72], [73], their integration to achieve sustainable hyperautomation has not been previously reported. Appendix 10 provides the mathematical basis of the DTs and models. The second block represents the intelligent Enterprise Management System (iEMS) that ensures a stable and optimal operation of the designed production system and supply chain, using feedback from actual physical produc- tion. The third block covers the analysis of production costs with respect to volumes, configuration requirements, degree of automation, analysis of the market state and competitors' proposals, and updating the references for the development block. The closed-loop interconnection of elements allows iterative optimization of the necessary parameters at the key steps. The following sections describe more specific aspects of the relationship between the development of a closed-loop system of digital tools and intelligent enterprise management systems. The set of interconnected digital tools for the entire business operation is represented at Figure 5, where the tools created in Diakont are highlighted.

A deep analysis of Figures 4 and 5 allows to identify one of the core aspects of the hyperautomation framework, describing the closed loop interconnection of the business functions and production system supported by digital tools completely designed and developed by the authors.

Another core novelty of the hyperautomation framework described here is the iEMS. It acts not only as a standard ERP (Enterprise Resource Planning) system, allowing for an operative control and management of the enterprise, but also covers the strategic and management decision-making level (through its ACS (Accounting and Control System), where the models, described below as parts of the DTs are performed).

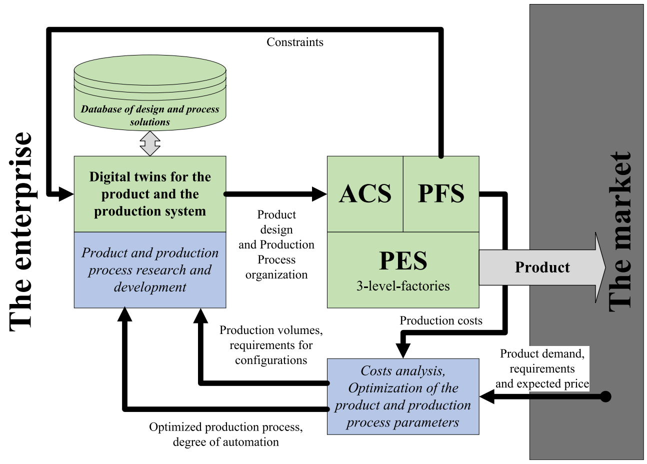


**FIGURE 4.** The system of digital tools that allows the design of the product with necessary parameters and provides the optimization of the production cost.

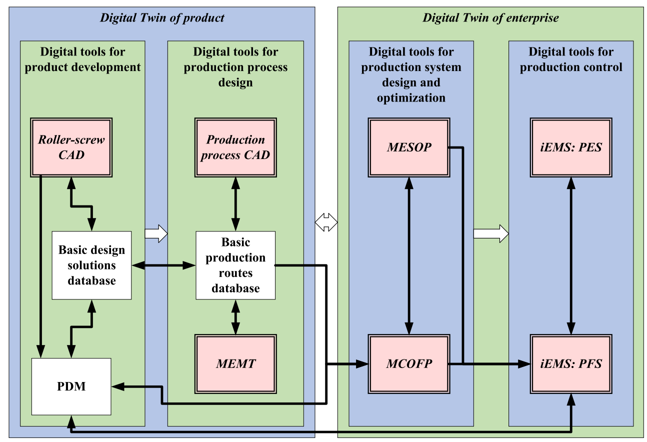


**FIGURE 5.** The set of interconnected digital tools for the entire business function.

### A. DTS OF THE PRODUCT AND PROCESS

The DT of the product includes a set of 5 digital tools for product development and the design of the production process (Figure 5). The Roller Screw Computer Aided Design (CAD) is a digital product sandbox used to determine geometric parameters (dimensions, shape of the surface), accuracy parameters (positioning precision), indicators of physical and mechanical characteristics, and the life cycle of key components of precision roller screw units. A Product Data Management (PDM) system is the DT of a product at the stage of its development and customization. Roller screw CAD significantly reduced the time of development and customization of the product. In particular, roller screw CAD has accelerated the development of new basic unified module roller screw gears. In addition, roller screw CAD allows virtual testing, thereby reducing the time to market. In addition to the digital sandbox, a real test site was created, including a production site, testing, and measuring base. The feedback obtained from a real test site was used to improve the relevant algorithms. The roller screw CAD is not just a separate tool, but an essential Digital Tool integrated into the company infrastructure, and a novel component of the hyper-automation framework. In this case, changes in the design parameters of the roller screw, will cause respective changes in the design of the LEMA, in the process and technology, and finally in production costs, and that goes authomatically. Developing and planning of the launch of new product into production is supported by an estimation of all the changes needed withing the production system and their influence on the economic parameters of the entire business at every stage.

CAD of the production process is a set of DTs for different processing methods used for product development. Depending on the design parameters, such as overall dimensions, manufacturing accuracy, and the number of processed surfaces, the CAD of the production process provides an estimate of the main technological parameters, such as processing, preparatory/final/auxiliary times, and complexity of operations. Process CAD contains a parameterized database of primary production and automation equipment and allows for a quick assessment of the new parameters of the technology if the equipment is changed. The main objective of this step is to develop a process that provides cost optimization, reduces the length of production cycles, ensures the stability and flexibility of the production process, and minimizes dependence on human mistakes [74]. This step also defines the methods and tools for automating the main and auxiliary operations of the production cycle, such as storage, transportation, machining, assembly, testing, measurement, and control and management processes. The Model for Evaluating Manufacturing Technologies (MEMT) is a digital tool for the comparative analysis of preferable design and technological solutions. It compares several variants of different designs and manufacturing technologies, provides the same technical parameters for the products, and defines the most cost- effective process. A database of standard manufacturing technologies was developed using the production process CAD and model of manufacturing technology evaluation. This database provides the most cost-effective production of standard design solutions and conformity of manufacturing technology for various product lines. The DTs of products and processes significantly augment the standard Product Lifecycle Management (PLM) practices used in the overall R&D process.

### B. DT OF THE ENTERPRISE

#### 1) PRODUCTION SYSTEM DESIGN AND OPTIMIZATION

The iEMS had three structural levels: strategic, operational, and execution (Table 3). A feedback-driven interaction between the DT of the production process and the produc- tion cost plays a key role in the complete automation of the production process (Figure 5 and 6). The Model of Evaluation of Solutions on the Organization of Production (MESOP) provides a comparative analysis of preferable organizational decisions, covering individual technologies and the overall parameters of the manufacturing system. Depending on the optimal manufacturing technology predicted by MESOP, a Model of Calculation, analysis, and Optimization of the Financial-economic Parameters of production (MCOFP) determines the number of personnel, equipment, and machines required for automation to reach a given sales volume. MCOFP also predicts fixed and variable costs and the average value of production costs using input cost data such as salaries and costs of materials and types of machinery, energy resources, and services obtained from a third party. The calculation is repeated cyclically with a specified increase in sales volume. Finally, based on the results of the model, a declining curve is formed that characterizes the average cost under specified conditions.

**TABLE 3. Structural organization and main tasks of the intelligent enterprise management system.**

| iEMS Levels | iEMS tasks |
|---|---|
| *Strategic level*: the accounting and control system (ACS). It applies to the production system as a whole and is used for the management and control of geographically distributed factories | Manages main technological and managerial competences and responsibility between the company headquarters and worldwide factories network – implemented by algorithms of planning and forecasting system<br>Allows to optimize the requirements to the number and expertise of managerial personnel |
| | Separates the management functions and process execution functions – implemented by models of planning and forecasting system that generate tasks for process execution system |
| *Operational level*: the planning and forecasting system (PFS). Part of the models of PFS operates with production system as a whole, while the other works for a separate fatory at its production site. Being based on the big data of the production system, the PFS provides automated and intelligent decision-making | Minimizes logistics costs and time for product delivery to the customer – implemented through modeling a supply chain in the planning and forecasting system |
| | Forms and executes the production program, ensuring minimal inventory at the factories of all the levels – implemented by modeling a master planning schedule in the planning and forecasting system |
| *Execution level*: the process execution system (PES) that extents to a single factory of production site and is closely integrated with Manufacturing Enterprise System (MES) and Building Management System (BMS) | Ensures accuracy, relevance and efficiency of obtaining data necessary for management decision-making<br>Collects data directly from the processes through data acquisition from involved personnel and connected machines |
| | Ensures economic consumption of resources by factories – implemented through interconnection between manufacturing program and factory systems (MES and BMS) |

#### 2) PRODUCTION CONTROL

Autonomous production control is achieved using an iEMS that integrates the planning and forecasting system (PFS) with

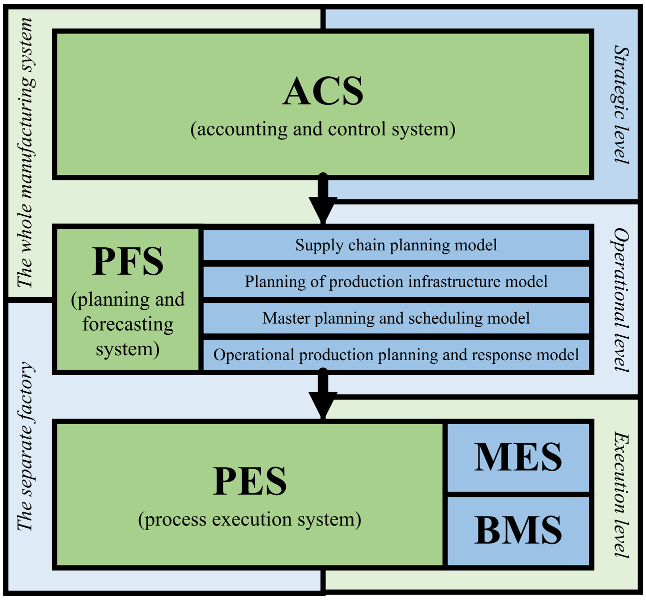


**FIGURE 6.** **Composition of the intelligent enterprise management system.**

the process execution system (PES). Using statistical and artificial intelligence-enabled analysis, the PFS automatically manages supply chain planning, delivery time minimization, master planning, scheduling, production infrastructure planning, operational production planning, andoperational production response (Figure 6). PES transfers tasks generated by the PFS to production resources and collects feedback on performance [75], [76], [77], [78]. PES promptly and adequately provides relevant information on the state of the production system and its resources. Feedback on the implementation of the production program forms the basis for the operational model of the production response of the PFS. The models inside the PFS are self-learning: they are calculating some ''ideal'' picture by means of the DT, but when the fact feedback differs from plan, they are estimating some coefficient / factors for their calculation, so in this way they are teached to be closer to the reality at the next step of calculations.

The end-to-end traceability of products in the manufacturing process is organized such that the PES is the digital shadow of the product instance in the manufacturing lifecycle phase [79]. In manufacturing, updated information can be obtained regarding the location and condition of each product. For each unit of finished products, it is also possible to obtain information about all its components, from the batches of materials and components from which they are made to the results of measurements and tests and climatic conditions at the time of manufacturing, which is ensured by integrating the production system with the management system of the ''smart building'' of the factory. This approach provides a wide range of opportunities for debugging processes on a virtual testbed, in close conjunction with their physical implementation.

## V. HYPERAUTOMATION FRAMEWORK: RESEARCH AND INNOVATION METHODOLOGY ALIGNED WITH INDUSTRIAL REFERENCE SPECIFICATION

Following the identification of the primary needs related to the development of a new product and its associated business, it is critical to identify the links between several natural problems, tasks, and parameters. The next step is to quantify and qualitatively analyze the technicality and underlying financial imperatives of these interconnections. This is followed by the development of a collection of models and tools for implementing all the interconnections and computations in a digital environment, while also devel- oping tools for early data gathering and incorporating these tools into the core processes. Solving the research/study problem was an important part of the process; thus, a large set of case data was analyzed, and then, based on the case data, a group of problem points that were more representative were selected and deeply analyzed, with the goal of creating a solution that avoids all representative problems. Indeed, a distinctive part of the research and innovation methodology is the direct application to the entire design and manufacturing process of a critical component in diverse cyberphysical systems, the Linear Electromechanical Actuator (LEMA).

To ensure a larger and higher effect on the existing industrial ecosystem, a major feature of the innovative approach is that the outcomes of development and implementation, as well as the related business framework, are completely aligned with commonly used industrial reference specifications. Following the digital transformation impulse carried out by two major representatives, industrial digitalization and networking initiatives such as the Industrial Internet of Things and Industry 4.0, it was decided to position the hyperautomation infrastructure within the Reference Architecture Model for Industry 4.0 (RAMI4.0) (DIN SPEC 91345:2016-05) [80], [81], [82], [2]. It is important to recall here that RAMI4.0 aims to formally specify industrial assets and asset combinations positioning them within a 3-dimensional space covering its/their position (1) within the Industrial Eco-System (Hierarchy-Dimension), (2) considering its/their LifeCycle (Value Stream-Dimension) and (3) providing the essential specifications for the digitalization, networking and service-based businesses (Layer-Dimensions) [10].

The position of Diakont's hyperautomation approach within the dimensions of the DIN SPEC 91345 RAMI4.0 is shown in Figure 7 for the manufacturing of LEMAs (CPSs). It should be noted that all architectural layers are digitalized, and the positioning of Diakont's digitization solution is performed for the distributed engineering phases with Diakont as the technology and solution provider, along with the different phases of the value stream and life cycle of the addressed asset (LEMA).

## VI. PRODUCTION COST AND RETURN ON INVESTMENT

The hyperautomation approach described in this work has a significant positive impact on production cost and overall returns on investment; however, the benefits of this approach

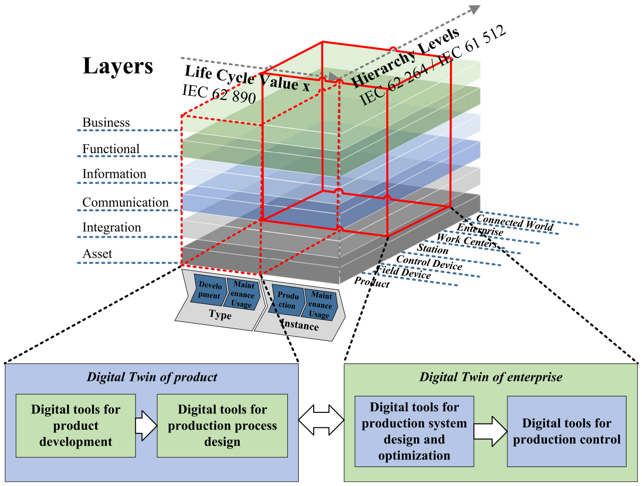


**FIGURE 7.** Digital tool set developed by Diakont positioned within the DIN SPEC 91345 RAMI4.0.

cannot be assessed by calculating returns solely based on projected cash flows and the discounted payback period. As classical models do not consider the capitalization of business and prospective market segments, forecast analysis using classical approaches may predict that establishing a new manufacturing unit using the proposed sustainable hyperautomation approach is a high-risk investment.

Therefore, in this work, to gauge the financial viability of the hyperautomation approach, the business development project for intelligent manufacturing of LEMAs was divided into four phases, spanning over 15 years (Table 4). The first phase integrates R&D and market entry. The second phase comprises investments in design and construction, organization, and equipment for distributed production, mainly performed following Industry 4.0-compliant digitalization and networking. In the third phase, batch sales commence. In the fourth phase, the volume of batch sales increases, and the results of investment made in the first three phases become evident. In particular, during the third phase, a reference point is established at which the assessment is made, and the intermediate result is summarized. To examine the effectiveness of the investment, it is necessary to consider all prospective market segments created during project implementation. Many of these market segments are unavailable if a traditional manufacturing approach is used. Furthermore, the progressive increase in production volumes in different implementation phases dynamically affects the manufacturing costs.

Figure 8 (a) shows the sales volume in the traditional market and Figure 8 (b) shows the increase in sales volume due to investments made in the first phase. Taking these two factors together, sales volume tends to saturate at approximately 12,000 units/year. Profiles 8 (c) and (d) reflect the effect of the initiatives taken in the second and third phases on sales volume - the discovery of new markets and creation of solutions based on the core product developed during the first phase are responsible for this synergistic effect. Furthermore, owing to the lack of competitive solutions, these new markets are characterized by higher growth rates (with certain inertia

**TABLE 4.** Phases of business development and their brief characteristics.

| # | Characteristics of the project phase | Phase duration (years) |
|---|---|---|
| 1 | Investment into R&D aimed at entering markets with existing competitors and product solutions (creation of product and technology basics). Product DTs. Equipment of the test site | 3 |
| 2 | Start of sales, customization of developed products for new customers. Investments into design and construction, organization and equipment of distributed production based on the principles of Industry 4.0, including the creation of process model and DTs. Investments into the market study for new markets with possible demand in the product based on the product and technology basics | 3 |
| 3 | Batch sales. Investment into R&D for solutions based on developed product basics to introduce products into new markets having no competitors. Pilot operation of the production system | 3 |
| 4 | Increasing the volume of batch sales, obtaining results of the investments of previous phases | 6 |

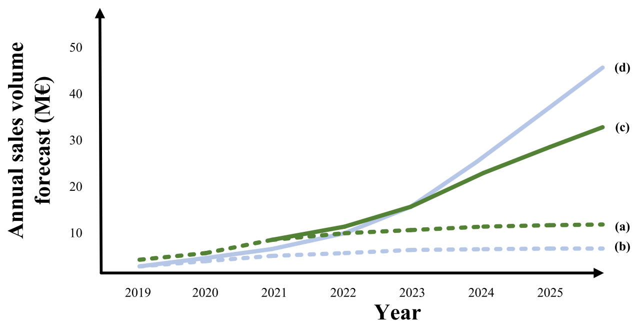


**FIGURE 8.** Forecast of sales dynamics under various scenarios.

in earlier stages) and larger volumes in the long term. Taken together, these factors provide the possibility of achieving sales volumes corresponding to the production volume of 50,000 units of standard products per year. The dependence of production costs on sales volumes is shown in Figure 9 for the various scenarios. These results were obtained using the MCOFP method described in the previous section.

Figure 9 (a) shows the production cost when universal Computer Numerical Control (CNC) machines are used, and Figure 9 (b) shows a scenario in which mass customization is performed with the use of specialized CNC machines. Figure 9 (c) represents the production cost when mass customization using specialized CNC machines is achieved with a high level of automation. Figure 9 (d) shows the production cost when the concept of a 3-level factory is implemented (intra-enterprise), along with the scenario mentioned in Figure 8 (c).

Brief analysis of Figure 9 shows that from an annual production volume bigger than 1,000 units per year (identified as point A), the use of universal CNC machines becomes less preferable than the other three described alternatives. With an annual production of more than 2,500 units the more feasible scenario is production using

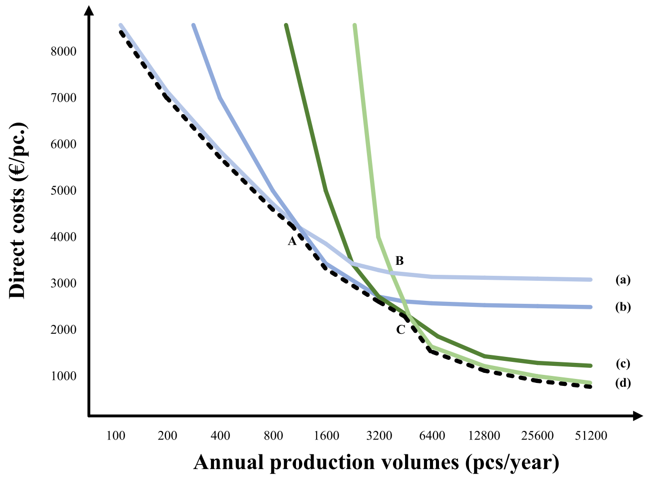


**FIGURE 9.** **Production cost for different production volumes under various scenarios (MCOFP results).**

automation.With an annual output of more than 6,000 units mass customization with specialized CNC machines automation, and 3-level factories, is feasible.

At an average market price of 1,500–1,600 EUR and a target cost of 1,000 EUR per unit of LEMA defined by the market, the operating profit of production begins only after a volume of 10,000 units per year (both in scenarios (c) and (d)). The production organization under scenarios (a) and (b) does not lead the business to operating profit. Despite the higher volume of capital costs and equipment for manufacturing sites in scenario (d), this option provides the fastest return on investment, especially in long-term sales forecasts. The annual output of 12,000 units forecasted based on the results of Phase 1 (the sum of the values for curves (a) and (b)) does not provide the minimal production cost (for scenario (d)) it is set even and slightly decreases starting from a production volume of 30,000 units per year), which shows the necessity of investment in Phases 2 and 3 of the projects. A combined scenario of production equipment, as shown in Figure 9 by a dotted line, is optimal. In Phase 1, production was implemented using universal equipment, starting with a volume of 1,000 units; special technologies were purchased and implemented. For production volumes of more than 2,500 units per year, an intelligent control system and automation were introduced into the production cycle. At volumes above 6,000 units per year, the mass production of LEMAs with 3-level factories becomes operational. This combined scenario minimizes capital and production costs in the initial stages of business development and reduces the payback period for investment.

## VII. CONCLUSION

Achieving sustainable automation in the manufacturing of high-tech products requires the seamless digital integration of various business functions and capabilities to make autonomous decisions at various levels, from the Operation Technology (OT) till the Information / Management Technology (IT) levels of an enterprise and out of the enterprise within the Supply Chain. This paper has provided the knowledge background, scientific, technical and business and technical background, which is basically necessary for achieving sustainable hyperautomation, with a real industrial application scenario in the manufacturing of cyberphysical actuators. The hyperautomation approach outlined in this study allows efficient interconnections between various control, automation, and business functions facilitated by the digitalization and networking of different industrial tools. Moreover, by uncovering and automating previously inaccessible data and processes, this approach also shows the unique benefit of creating a set of Digital Twins, provided by these tools and positioned within the real industrial engineering, automation and management infrastructure inside a real industrial organization. It has also been shown that the promotion of definitive designs based on unified solutions for typical and specialized applications is an effective strategy for achieving mass customization while retaining a sufficiently high production volume. The paper presented a set of industrial-mature digital tools formally positioned within the company infrastructure, according to the DIN SPEC 91345 RAMI4.0. This digitalization approach also allows online monitoring of market changes and provides optimized feedback that can be used for responsive digital modeling of the entire production process and associated businesses, within the company and out of the company within the connected digital world represented by the Supply Chain.

At this point, it is important to reinforce the fact that the applicability and particularly the impact of the hyperautomation approach discussed in this paper has been validated based on real experience with hyperautomation implementation at Diakont premises. Moreover, shown in the Table 1, the authors were able to compare the properties of frequently reported hyperautomation approaches with the major characteristics of the framework provided in this study for sustainable hyperautomation, identifying the differences and highlighting the novel aspects introduced in this manuscript.

On a holistic level, this paper has illustrated the key aspects of attaining long-term sustainable growth in the manufacturing of high-tech equipment by using mass customization, cutting-edge technology in the production process, and system-wide interconnected digital tools. The use of mathematical models for market forecasting, which are regularly updated by feedback from the market and customers, provides valuable knowledge on potential pro- duction volume and product cost estimates, enabling a fine balance in demand and supply. Responsive R&D, which can rapidly adapt to changes in production requirements and product features, is another central feature of the proposed approach. Mass customization is supported by a modular design approach that can provide up to 1000 variants of the product, whereas individual designs are used to produce definitive segments. Hyperautomation using digital twins of product and production processes, forecasting models, and interconnected enterprise management systems provides all-pervasive synergy across the entire business function. Although the present study focused mainly on hyperautoma- tion in the manufacturing of LEMA with RSG, the core concepts of the hyperautomation framework presented in this manuscript have also been employed by the authors in the manufacturing of components of CPS, such as feedback sensors, servo drives, and electric motors.

The production cost analysis suggested that the hyperautomation approach can reduce production costs to a substantially low level. However, our study suggests that to obtain such a competitive edge, responsive R&D and the implementation of intra-enterprise 3-level manufacturing concepts in a digitalized and networked Industry 4.0-compliant "connected world", as well as mass customization and a high degree of automation, are required. This encompasses conducting research and innovation with specialized machines and employing the coordinated use of multiple data processing technologies and tools, such as Industrial Artificial Intelligence (IAI) [83], machine learning, Business Process Management (BPM), and intelligent business process management suites (iBPMS), introduction of adequate Edge/Cloud technology [8]. Another avenue for further research, especially for innovating beyond the results presented by the authors, is the alignment of the hyperautomation framework with other industrial reference specifications than RAMI4.0, particularly with regard to the business values in differ- ent manufacturing sectors in different parts of the world, such as the alignment with Industrial Internet Reference Architecture [84]. Furthermore, although the findings presented in this article are discussed with a focus on a real industrial LEMA production, similar approach and associated framework enlarged with appropriate adjustments may also be implemented in other industrial production sectors and other high-tech business areas such as transportation, energy, etc [82].

## APPENDIX

## MATHEMATICAL MODELS USED IN DIGITAL TOOLS

To support the process of organizational decision-making at the top level, a mathematical model based on the linear programming problem is used. As the bases around which the restriction system is built, the following data on possible production processes and availability of production infrastructure is used: $\sum_{ij} t_{ij}x_{ij} + c_{ij} = T_j$, where $t_{ij}$ is the processing time for the $j$-th resource, when using the $i$-th process route, $T_j$ is the available labor time founds of the $j$-th resource, $x_{ij}$ is the unknown representing the number of parts manufactured using the $i$-th route, $c_j$ is the unknown representing the downtime of the resources. The number of equations in the system will correspond to the number of types of available resources, and the number of the unknowns will be equal to the number of all possible routes, plus the variables representing the resource downtime. Depending on the specific formulation of the problem, the objective function is built and additional equations are introduced into the set of constraints, for example, the ones requiring the delivery of the complete number of kits, rather than individual parts. To find the maximum (or minimum) of the function under the given constraints, we use the simplex method, which allows us to perform calculations rather fast even at a very large dimension of the problem.

This approach, based on a single database of available optional solutions, allows, for example:

- To choose the routes for manufacturing of product components that will provide minimum costs at maximum throughput among other available routes, considering the available production resources and infrastructure, the organization of production processes and the level of automation;
- To calculate and optimize such parameters as the number of production staff, the number and modes of operation of machine tools considering the available production infrastructure, ways of organization of production processes and the level of automation;
- To compare several options for the organization and automation of production processes;
- To check the sustainability of the production system to the changes in batch sizes and product customization grade.

To obtain all these solutions, we use a number of optimization problems from linear programming, united by a common set of constraints. Also, the model for evaluationg solutions on the organization of production performs the function of checking the balance of production resources under conditions of multiple-machine service mode of the production operators. In our opinion, such addition is essential for organization of automated production of the smart factory, since with a high degree of automation operators are no longer assigned to the machines and act like an additional restriction when scheduling the operations. No scheduling system can provide perfect schedules that would ensure accurate timing of production tasks for machines and personnel, which can lead to either machine downtime while waiting for the setup or excessive staff and overstating production costs when operators maintain machines in multiple-machine mode. Thus, there is a problem of defining the balance of production resources.

The developed model of checking the balance of production resources for modeling possible losses uses an approach based on Markov's theorem. A Markov process with $N$ discrete states is modeled for the considered production area. One of the states corresponds to the need for intervention of the operator into the process, while all the others correspond to the maintenance of one of the machine units and a combination of machines in the service queue. A system of Kolmogorov's equations is compiled:

$$\frac{dP_i}{dt} = -P_i\,(t) \sum\nolimits_{j;j\neq i} \lambda_{ij} + \sum\nolimits_{k;k\neq i} P_k(t)\mu_{ki},$$

where $P_i$ and $P_k$ stand for probability of the corresponding state of the system, $i, j \in \overline{1, N}$, $\lambda_{ij}$, $\mu_{ki}$ stand for intensity of the transition from state $i$ to state $j$ and from $k$ to $i$. For ultimate probabilities, where $\frac{\partial P_i}{\partial t} = 0$, we obtain the system of linear equations, that is easily solved if it is supplemented by the requirement that at any given time it is in one and only one of its states: $\sum_k P_k = 1$.

Thus, we will obtain the probabilities of the states of the system, that is, for a sufficiently long period of time, we will find out the average time spent by the system in each of them, from which it will be possible to conclude whether there are enough operators for the machines fleet in problem, and whether the machines fleet itself is sufficient with such a number of the operators. The source data for this model, in additional to the general schedule parameters, are detailed process maps of each of the company's processes that require for production resources.

## AUTHORS' CONTRIBUTIONS

Mikhail E. Fedosovsky: Conceptualization, Writing, Original Draft Preparation

Mikhail M. Uvarov: Formal analysis and investigation, Writing - original draft preparation

Sergey A. Aleksanin: Writing, Review, and Editing

Anton A. Pyrkin: Writing - review and editing

Armando Walter Colombo: Supervision

Domenico Prattichizzo: Review and editing

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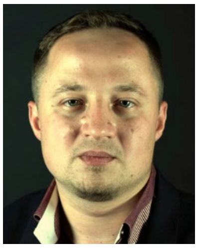
**MIKHAIL E. FEDOSOVSKY** was born in Uzbekistan, in 1959. He graduated from the Leningrad Institute of Technology, Leningrad, Russia, in 1983. He received the Ph.D. degree in safety in emergency situations with the thesis of safety of nuclear fuel reloading at power units with pressurized water reactors, in 2009.

He is currently an Initiator of the Diakont Group and the Head of the ITMO University Department named the Institute of Intelligent Industrial Technologies in collaboration with Diakont. He is the author of more than 30 academic articles, including ten industrial patents. His research interests include probabilistic safety analysis, safety, and security of industrial objects.



**MIKHAIL M. UVAROV** was born in Saint Petersburg, Russia, in 1983. He received the M.S. degree in computer science from ITMO University, Saint Petersburg, in 2006.

Since 2004, he has been working with Diakont and now heading its IT Department. Since 2012, he has been a Lecturer with ITMO University. He is currently the Leader of the project for development of the intelligent enterprise management system with Diakont. He is the author of several academic publications dedicated to information management. His research interests include computer and information science, data analysis, mathematic modeling and optimization, and production management.

**SERGEY A. ALEKSANIN** was born in Norilsk, Russia, in 1977. He graduated from Saint-Petersburg Polytechnical University, Saint Petersburg, Russia, in 2000. He received the Ph.D. degree in design automation system with the thesis of designing methods for automated image processing for defectoscopy systems, in 2017.

In Diakont, he leads the department dedicated to the production process automation. His research interest includes automatic design and manufacturing.

**ANTON A. PYRKIN** was born in Zaozerniy, Russia, in 1985. He received the B.S., M.S., Ph.D., and Doctor of Science (Habilitation Thesis) degrees in system analysis, data processing and control from ITMO University, St. Petersburg, Russia, in 2006, 2008, 2010, and 2015, respectively.

He has been a Leading Professor and the Dean of the Faculty of Control Systems and Robotics, ITMO University, since 2016. He is the coauthor of more than 200 publications. He possesses a wide experience in initiation and management of research and development projects dealing with control science, automation, robotic, and mechatronic systems. His research interests include adaptive and robust control methods, hybrid (switching, iterative) control and estimation approaches, disturbance estimation and cancellation, and control problems for plants with long input and state delays.

Dr. Pyrkin has been a member of the Technical Committee of the International Federation for Automatic Control IFAC TC 1.2 Adaptive and Learning Systems, since 2019, and a member of the Editorial Board of *Journal of Instrument Engineering*, since 2020. He is a member of the International Academy ''Navigation and Motion Control,'' since 2017.

**ARMANDO WALTER COLOMBO** (Fellow, IEEE) received the B.S. degree in electronics engineering from the National Technological University of Mendoza, Argentina, in 1990, the M.S. degree in control system engineering from the National University of San Juan, Argentina, in 1994, and the Ph.D. degree in engineering (manufacturing automation and systematization) from the University of Erlangen–Nuremberg, Germany, in 1998.

From 2001 to 2018, he worked as the Manager for Collaborative Innovation Programs and also as an Edison Level 2 Group Senior Expert at Schneider Electric Corporation. He joined the Department of Electrotechnical and Computer Sciences, University of Applied Science Emden/Leer, Germany, where he became a Full Professor, in 2010, and the Director of the Institute for Industrial Informatics, Automation and Robotics (I2AR), in 2012. He has over 20 industrial patents and more than 300 peer-reviewed publications. With his contributions, he has performed scientific and technical seminal contributions that are nowadays being used as one of the bases of what is recognized as ''The 4th Industrial Revolution.'' He is listed in Who's Who in the World/Engineering 99-00/01 and in Outstanding People of the XX Century (Bibliographic Centre Cambridge, U.K.). His research interests include industrial cyber-physical systems, industrial digitalization, engineering of industry 4.0.-compliant solutions, system-of-systems engineering, the Industrial Internet of Things, and intelligent production automation systems.

Dr. Colombo is a Senior AdCom Member of the IEEE IES, as well as a member of the European Public Policy Committee (EPPC) of IEEE. He is working as an Expert in the KDT-JU ECSEL as well as in the REA of the European Union and EUREKA programs. He is currently the Co-Editor-in-Chief of the IEEE Open Journal of the Industrial Electronics Society (OJIES) and a Distinguished Lecturer of the IEEE Systems Council.

**DOMENICO PRATTICHIZZO** (Fellow, IEEE) received the M.S. degree in electronics engineering and the Ph.D. degree in robotics and automation from the University of Pisa, Pisa, Italy, in 1991 and 1995, respectively.

In 1994, he was a Visiting Scientist with the MIT AI Laboratory. Since 2009, he has been a Scientific Consultant with the Istituto Italiano di Tecnologia, Genova, Italy. He is currently a Professor of robotics with the University of Siena, Siena, Italy. He is the Leader of a research unit in several EU projects. He is also the Co-ordinator of an EU ECHORD-EXPERIMENT and an EU IP Collaborative Project. He has authored more than 2000 articles in his research field. His main research interests include haptics, grasping, visual servoing, mobile robotics, and geometric control.

Dr. Prattichizzo was a recipient of the IEEE 2009 Chapter of the Year Award. He was the Vice Chair of the Special Issues of the IEEE Technical Committee on Haptics, during 2006–2010. He was the Chair of the Italian Chapter of the IEEE RAS, during 2006–2010. He has been the Chair of the IEEE RAS Early Career Awards Evaluation Panel, since 2013.